Predictability in the New Zealand Stock Market

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Abstract

Recent financial literature suggests that the variation in the dividend–price ratio is significantly related to the expected returns but not to the expected dividend growth. In other words, stock returns are predictable but dividend growth is not. However, most of this evidence comes from the U.S. at the aggregate level, and there is a lack of research that relates to this topic in the New Zealand stock market. This research examines the predictive power of the dividend–price ratio using New Zealand stock market data from 1931 to 2012. The results confirm the claim in the U.S data that returns are predictable but dividend growth is not in the New Zealand stock market data. This research also investigates whether the return predictability is associated with risk-pricing or mispricing; whether the return predictability is due to the fundamental relationship among the dividend–price ratio, future returns and future dividend growth, or whether it is due to the effects of historical events; whether out-of-sample forecasts will have the same patterns as in-sample predictions; and whether individual company returns are predictable.

Chapter 1 Introduction

The predictability of stock market returns has become one of the most popular research topics in finance. This is not surprising, because return predictability is of interest to practitioners and it also has important implications for asset pricing for academics. The literature on return predictability has evolved significantly since late 1980s; in particular, return predictability became the winning topic of the Nobel Prize in Economics in 2013.[1] Testing stock market predictability was originally motivated by testing market efficiency. It was generally considered that return predictability would be inconsistent with the constant expected returns and the efficient market hypothesis. The efficient market hypothesis suggests that stock prices reflect all the available information. Therefore, stock returns follow a "random walk" pattern: though there are long sequences of positive and negative returns in history, the expected future return is always about the same. Using patterns from past returns to forecast the future returns is useless, as "*any apparent predictability is either a statistical artefact which will quickly vanish out of sample or cannot be exploited after transaction costs"*(Cochrane 1999).

The possibility that stock returns can be predicted seemed unthinkable until the late 1980s, when several research papers started to document that stock returns were somewhat predictable (Campbell and Shiller, 1988a and 1988b; Fama and

[1]The Nobel Prize in Economics 2013 was awarded jointly to Eugene F. Fama, Lars Peter Hansen and Robert J. Shiller for their significant contribution to return predictability research.

French, 1988a and 1988b). Since then, many researchers have begun to explore stock return predictability. Over the years, many variables have been found to have predictive power for stock returns. Most of these variables can be categorised into macroeconomic variables and valuation variables. On one hand, macroeconomic variables such as interest rates (Ang and Bekaert, 2006; Campbell, 1991; Ferson, 1989), inflation (Fama, 1981; Rapach *et al*., 2005), the industrial production index (Rapach *et al*., 2005), the consumption–wealth ratio (Lettau and Ludvigson, 2001) and the aggregate investment–capital ratio (Cochrane, 1991) are suitable for stock return predictions because the expected returns are usually highly correlated with the condition of the economy. For example, during economic downturns, the high risk-aversion of investors results in a high risk premium and hence the expected returns are high, and *vice versa* (Lettau and Ludvigson, 2001).

On the other hand, valuation variables such as book-to-market ratios (Fama and French, 1992; Pontiff and Schall, 1998), dividend–price ratios (Campbell and Shiller, 1988a and 1998; Cochrane, 2008; Fama and French, 1988a) and earnings–price ratios (Campbell and Shiller, 1988a and 2001) have significant predictive power for stock returns because these ratios relate to both rational pricing and mispricing theories. For instance, the rational pricing view says that the ratios are associated with the time variation in discount rates. The ratios are positively correlated with discount rates and can therefore predict returns, based on the information reflected by the ratios on the risk premium.

Furthermore, the mispricing theory suggests that the ratios are high when the stocks are underpriced relative to their fundamental values. As investors realise this, prices adjust to their fundamental values and hence returns will be high, as predicted by earlier ratios.

However, most of the evidence is from the U.S. and there have not been many studies that relate this topic to the New Zealand stock market. The first part of this thesis aims to bridge this gap and provides some New Zealand return predictability evidence using New Zealand stock market data from 1931 to 2012. Chapter 2 reviews the relevant literature and discusses the controversies in the literature. Chapter 3 presents the theoretical background and the empirical methods. Chapter 4 contains a description of the data. Chapter 5 provides estimation results and an interpretation. Specifically, Chapter 2 to Chapter 5 are closely related to a branch of the return predictability research that has received a lot of attention in the literature (e.g., Cochrane, 1992, 2008 and 2011b; Lettau and Van Nieuwerburgh, 2008; Chen, 2009; Binsbergen and Koijen, 2010). This branch of research investigates stock return predictability using dividend–price ratios at the aggregate level by incorporating the restrictions associated with the Campbell and Shiller (1988a) present value relation. This branch of research also argues that return predictability driven by dividend–price ratios must be studied jointly with dividend growth predictability, because dividend–price ratios should forecast at least one of these two variables.

Moreover, to provide more convincing results, this thesis follows Cochrane (2008, 2011b), Lettau and Van Nieuwerburgh (2008), Chen *et al.*(2012) and others by using both a direct approach and a first-order vector autoregressive (VAR) approach to examine the predictability of the dividend–price ratios in the New Zealand stock market. The direct approach estimates univariate regressions of future returns and dividend growth on the current dividend–price ratios. The VAR approach investigates the predictability using first-order VAR representations of the returns, dividend growth and dividend–price ratio persistence. The difference between the two approaches is that the direct approach might provide more accurate estimates than the VAR approach if shocks in the current dividend–price ratio have long-lasting effects on the future returns or dividend growth. This is because the first-order VAR model might fail to capture any long-lasting effects, as there are restrictions imposed in the model. On the other hand, the VAR approach might provide better finite-sample properties, thus giving higher power against the null hypothesis of no predictability.

Furthermore, unlike the traditional return predictability research, which usually uses up to a certain number of years as the regression horizon, the use of the first-order VAR approach allows us to examine the statistical power and economic significance of the return or dividend growth predictability at very long horizons. Very long horizon regressions carry more statistical power and economic significance than short to intermediate horizon regressions because the high persistence of dividend–price ratios tends to outweight return or dividend growth predictability at short to intermediate horizons. This thesis also investigates the excess return predictability because it has also been the focus of the predictability literature (excess return predictability is jointly examined with excess dividend growth predictability). This thesis confirms the general findings of Cochrane (2008 and 2011b) in the New Zealand context:

i) The real and excess returns are predictable at short, medium and long horizons, but real and excess dividend growth are not.

ii) The real and excess return predictability increases with the horizon.

The return predictability research has also raised some interesting questions: Is the return predictability associated with risk-pricing or mispricing? Is the return predictability caused by the fundamental relationships among the dividend–price ratio, future returns and future dividend growth? Or is it caused by the effects of historical events? What do out-of-sample forecasts look like? Are individual company returns predictable? It seems that there have not been many studies covering these questions in the New Zealand stock market. The second part of this thesis will address these questions.

Chapter 6 answers whether return predictability is associated with risk-pricing or mispricing. The whole sample is divided into two subsamples (1931–1984 and 1985–2012) distinguishing the periods before and after New Zealand financial sector reform in 1984. As the reform effectively removed many restrictions on information flows that encouraged mispricing, the degree of mispricing in the post-reform sample should be lower than that in the pre-reform sample. If the New Zealand return predictability is due to mispricing, one would expect to see a stronger relationship between dividend–price ratios and future stock returns in the pre-reform sample and a weaker relationship in the post-reform sample. On the other hand, if the return predictability is due to risk-pricing, the financial sector reform should have no effect on the relationship between dividend–price ratios and future stock returns. By comparing the return coefficients of the two subsamples, this chapter finds that the return predictability in the New Zealand stock market is not primarily due to mispricing.

Chapter 7 examines whether the return predictability is primarily due to fundamental relationships among the dividend–price ratio, future returns and future dividend growth, or whether it is due to the effects of historical events. To investigate which is the primary cause in the New Zealand stock market, I follow the idea of Cornell (2013 and 2014). A linear trend is used to represent the fundamental equilibrium values of dividend–price ratios over the sample period, followed by a regression model of the stock returns on the differences between the actual dividend–price ratios and the equilibrium dividend–price ratios. The purpose of this method is that when most of the fluctuation in dividend–price ratios is caused by historical events, using the difference between the fundamental equilibrium values of the dividend–price ratio and the actual values of the dividend–price ratio as the explanatory variable should lead to an increase in the return regression estimates. By comparing return estimates that use the actual dividend–price ratios as the explanatory variable, the results indicate that the observed return predictability in the New Zealand stock market is caused by historical events.

In addition to examining the in-sample predictability, Chapter 8 examines the out-of-sample predictive power of dividend–price ratios. Following the approach of Goyal and Welch (2003), the out-of-sample forecasting power of dividend–price ratios is compared with the forecasting power of the sample means. The results show that unlike the out-of-sample tests on the U.S. data, which commonly report poor out-of-sample predictability for dividend–price ratios, dividend–price ratios have strong out-of-sample predictive power for real returns at short, medium and long horizons. Dividend–price ratios also show some good out-of-sample predictive power for excess returns at short to medium horizons.

Chapter 9 investigates the predictability of dividend–price ratios down to the individual firm level using data from four New Zealand companies that have been listed continually since as far back as 1964. The results suggest that the predictability evidence is mixed. Future returns are highly predictable at different horizons for some companies. On the other hand, for other companies, both returns and dividend growth are predictable, or dividend growth alone is predictable. The mixed evidence suggests that the conclusion that return predictability is the main driver of variation in the dividend–price ratios of the aggregate market portfolio does not apply at individual firm level. The dividend growth predictability disappears at the aggregate level because the predictable component for each individual company is diversified away when it is aggregated in an index portfolio (Bali et al., 2008; Vuolteenaho, 2002). Furthermore, the results also confirm the claim by Cochrane (2008) that dividend–price ratios must predict returns or dividend growth or both, and that there must be a fundamental relationship among expected returns, future dividend growth and dividend–price ratios.

Chapter 2 Relevant Literature

Before the late 1980s, the predictability of stock returns was considered to be impossible. Although some researchers such as Ball (1978) and Rozeff (1984) argued that the dividend–price ratio could be used to forecast returns, their work did not provide strong support for return predictability. In the late 1980s, Fama and French (1988a) and Campbell and Shiller (1988a) published perhaps the two most influential papers in the return predictability literature. Their studies have changed the traditional view of stock return predictability towards the opposite direction. They found that that dividend–price ratios, in aggregate stock portfolios, have strong predictive power for returns, especially over long horizons. Since then, the return predictability of dividend–price ratios on returns has received a lot of attention and the topic has been re-examined extensively (e.g., Cochrane, 1992, 2008 and 2011b; Lettau and Van Nieuwerburgh, 2008; Chen, 2009; Binsbergen and Koijen, 2010). The intuitive thinking around dividend–price ratios and how they forecast stock returns is that stock prices are high relative to dividends when the expected returns are low, and *vice versa*. Therefore, dividend–price ratios vary with expected returns. Cochrane (2011a, Ch.20) explained that if we do not rely on any asset pricing model, dividend–price ratios can only move if they forecast expected future returns, if they forecast expected future dividend changes or if prices change only in response to news about their future values, a.k.a. “rational bubbles”.[2] A general

[2] Cochrane (2011a, Ch.20) provides an excellent discussion on the issue of “rational bubbles”

conclusion in the literature is that almost all the variation in the dividend–price ratio is caused by changes in return forecasting, not dividend growth forecasting and not "rational bubble" forecasting (summaries of this evidence can be found in Cochrane (2008, 2011a and 2011b), and Koijen and Van Nieuwerburgh, 2011). Given this significant amount of empirical evidence, the view of stock return predictability has changed to the opposite direction to what the efficient market hypothesis suggested. The hypothesis that stock returns are predictable (especially at long horizons) has been widely accepted and it has been called a "new fact in finance" by Cochrane (1999).

However, this "new fact in finance" has also caused a lot of controversy because the forecasting relationship between dividend–price ratios and future stock returns displays some problems. The first issue is that standard tests in the return predictability literature are argued to be somewhat problematic. Ang and Bekaert (2006) argue that the standard approach in the literature (see, for example, Campbell and Shiller, 1988a; Campbell and Viceira, 1999; Stambaugh, 1999), which uses univariate dividend–price ratio regressions to compute expected returns, may not provide accurate estimates. This is because a linear or a VAR system cannot fully capture the non-linear dynamics of the data-generating process for returns, dividend–price ratios and changes in dividends. Ang and Bekaert (2006) built a non-linear present value model in which the dividend–price ratio was a highly non-linear function of the interest rate, excess returns and cash-flows. They found that univariate dividend–price ratio regressions provided a poor proxy for true expected returns. Their results also indicated that predictability generally occurred at short horizons rather than at long horizons. The predictive power of dividend–price ratios only appeared to be strong in a bivariate regression with short-term interest rates at short horizons. Additionally, in the bivariate regression, most of the predictive power came from the short-term interest rates rather than from dividend–price ratios. Moreover, they found that dividend–price ratios had good predictive power for future interest rates and dividend growth but very little predictive power for returns. Thus they concluded that under a non-linear present value model, the return predictability we see in the mainstream literature that used univariate linear models was simply not there, as univariate linear models of the expected returns were likely to fail to capture the important predictable components in returns.

Valkanov (2003) demonstrated that long-horizon regressions would always produce statistically significant results in finite samples, whether or not there was a structural relationship between or among the underlying variables. To understand this conclusion, he explained that "*in a rolling summation of series integrated of order zero (or I(0)), the new long-horizon variable behaves asymptotically as a series integrated of order one (or I(1)). Such persistent stochastic behaviour will be observed whenever the regressor, the regressand, or both are obtained by summing over a nontrivial fraction of the sample.*" (Valkanov, 2003, pg202). This rolling summation process in long-horizon regressions changes the stochastic order of the variables and this causes poorly distributed slope estimators, *t*-statistics and R^2 values. Based on this idea, he used the Functional Central Limit Theorem to examine the distributions of *t*-statistics from the long-horizon regressions that were usually used in the literature. He found that the *t*-statistics in long-horizon regressions were not well distributed with enough power and size. Furthermore, the ordinary least squares estimator was not consistent and the R^2 value was not a good indicator of the goodness of fit under some circumstances.

Valkanov applied his method to the U.S. data, the result of which stood in contrast to studies such as those of Fama and French (1988a), Campbell and Shiller (1988a), and Hodrick (1992). Using the whole sample period (1927–1999), it failed to reject the null hypothesis of return predictability at any horizon. Moreover, by looking at the different subsamples, the findings were consistent with those of Goyal and Welch (2003): the only piece of evidence of return predictability came from the 1946–1980 sample. Therefore, it was concluded that when more accurate testing methods were applied, return predictability did not appear to be as strong as previously suggested and therefore the results from long-horizon regressions should be carefully re-examined.

In contrast to Valkanov (2003), Ferson *et al.*(2003) developed a framework that focuses on short-horizon regressions. They focused on the problems that spurious regression bias and data mining raise. Spurious regression bias is related to the studies such as those of Yule (1926), and Granger and Newbold (1974). These studies argued that spurious relations may exist between the levels of non-stationary time series that are independent. For example, it is possible that a regression of one independent random variable on another random variable will still produce a significant coefficient. In the return predictability literature, the dependent variable is asset returns or excess returns, which are not highly persistent. Therefore, one might think that spurious regression bias should not be an issue. However, asset returns are expected returns plus unpredictable noise. If the underlying expected returns are persistent, spurious regression bias could potentially still be an issue because the unexpected noise may have a major influence on the variance of stock returns.

Ferson *et al.*(2003) examined the results of the univariate regression in nine of the major predictability studies (e.g., Fama and French, 1988a; Lettauand Ludvigson, 2001). They found 7 of the 17 *t*-statistics and R^2 which were statistically significant by the 5% criteria in those studies became insignificant after taking spurious bias into account. Therefore, they suggested that we should be careful when we use lagged instruments to model time variations in expected returns. When lagged instruments are used to investigate an asset pricing model, the spurious regression problem could lead to serious problems.

Data mining issue was studied for stock returns by Lo and MacKinlay (1990), Foster *et al.*(1997) and others. Ferson *et al.* explained that if the predictive variables that yield high R^2 values are mined and used in the predictive regressions, this data-mining effect was more likely to produce the spurious regression problem. They indicated that many of the standard predictive variables in the literature were actually highly auto-correlated, which was an indication that they could be from a spurious mining process. Their simulation results also suggested that many of the predictive variables in the literature may be spurious as well.

Furthermore, because dividend–price ratios are generally highly persistent, the correct means of statistical inference is problematic. In the predictability literature, standard tests usually allow the possibility of a unit root. However, many studies such as those of Ang and Bekaert (2006), Nelson and Kim (1993), Stambaugh (1999) and Valkanov (2003) pointed out that the statistical evidence of predictability became weaker when the tests were adjusted for the high persistence of dividend–price ratios.

The second issue is that dividend–price ratios are argued to have poor out-of-sample forecasting power,[3] as shown in Bossaerts and Hillion (1999), and Goyal and Welch (2003). Goyal and Welch (2003) focused on the out-of-sample

[3]The terms “forecast” or “predict” are sometimes ambiguous in the literature. Most papers use “forecast” or “predict” to refer to the in-sample fit of the regressions using the whole sample. Predictions using only prevailing data are referred as “out-of-sample forecasts” or “out-of-sample predictions”. This thesis follows this convention.

predictability of dividend–price ratios and found that return forecasts based on dividend–price ratios and a number of similar variables do not work out of sample. They compared return forecasts at *t+1* produced by estimating the regression using data up to *t,* with return forecasts that used the prevailing sample mean, and found that the prevailing sample mean had more out-of-sample predictive power than the dividend–price ratio. Bossaerts and Hillion (1999) examined the out-of-sample predictability of dividend–price ratios using international data. They constructed various models based on different model selection criteria, such as the Akaike Information Criterion, the Bayesian Information Criterion and the Focused Information Criterion, and found that none of the models that the selection criteria chose generated significant out-of-sample forecasting power.

Return predictability seems doubtful, as there has been an increasing number of studies questioning the predictive power of dividend–price ratios. However, Cochrane (2008) argued that there are some common misunderstandings in the literature and most of the studies against return predictability is caused by these misunderstandings. He provided arguments that strongly support return predictability and discussed these misunderstandings in depth.

Firstly, Cochrane (2008) argues that most studies that find no advantage to long-horizon regressions usually use finite horizon regression coefficients and direct regressions. He compared the results between finite and infinite horizon regression coefficients, and concluded that long-horizon regressions have greater power to reject the null hypothesis of unpredictable returns, but this power only occurs and increases beyond the 5-year horizon for the U.S. data. Also, instead of using direct long-horizon regression coefficients, he used implied coefficients, which are first-order VAR coefficients. Introducing first-order VAR coefficients eliminated the uncertainty that direct regressions have and increased the predictive power for long-horizon regressions.

Secondly, responding to the poor out-of-sample performance found by Bossaerts and Hillion (1999), and Goyal and Welch (2003), Cochrane (2008) explained that the correct interpretation of their findings is that regressions using dividend–price ratios are not very useful for making real-time forecasts, given the difficulty of accurately estimating the coefficients in the limited sample period. The poor out-of-sample forecasts do not mean that returns are unpredictable. Out-of-sample forecasting is not a more advanced test statistic that gives more convincing evidence about return predictability than the in-sample regression coefficients or other standard tests. He argues that "*One can simultaneously hold the view that returns are predictable, or more accurately that the bulk of dividend yield movements reflect return forecasts rather than dividend-growth forecasts, and believe that such forecasts are not very useful for out-of-sample forecasting and portfolio advice, given uncertainties about the coefficients in our datasets*." (Cochrane 2008, pg. 1566)

Finally, Cochrane (2008) concluded that the focus of return predictability should be on the hypothesis tests, not the point estimates. While point estimates can be biased and remain anyone's guess, hypothesis tests indicate the probability that the point estimates occur by chance if the returns are really unpredictable. Even if the chance of doing so is small, zero return predictability is not a very likely conclusion of the data in the literature. If returns really are unpredictable, dividend changes must be predictable in order to produce the observed variation in dividend–price ratios. However, empirical studies (e.g., Campbell and Shiller, 1988a and 1998; Campbell and Ammer, 1993; Cochrane, 2008, 2011b; Maio and Santa-Clara, 2013) found weak evidence that variation in dividend–price ratios is associated with variation in dividend changes. A null hypothesis in which returns are unpredictable must also specify that dividend growth is predictable: if dividend growth and expected returns have no effect, what does move prices? Return predictability is not a comforting result (at least not yet) and all we have learnt so far is that observed return predictability seems to be just enough to account for the variation in dividend–price ratios. If both future return and future dividend growth were unpredictable, we would have to believe that prices are moved by "bubbles", changing only on news about their future values.

In summary, the hypothesis that stock returns can be predicted by financial ratios like dividend–price ratios at the aggregate level has become widely accepted and has caused a new wave in finance. The topic of return predictability is still incomplete. There is literature questioning the standard statistical inference and the out-of-sample performance of the dividend–price ratios. However, statistical issues and poor out-of-sample performance do not mean we can conclude that returns are still unpredictable. Even if the standard return predictability tests like that of Fama and French (1988a) are statistically insignificant, we would have to believe that the volatility tests that won a Nobel Prize for Robert Shiller in 2013 are wrong. If returns are really unpredictable, dividend growth must be predictable in order to produce the observed variation in dividend–price ratios. We cannot conclude that dividend growth is predictable either, because the evidence that market dividend–price ratios are associated with subsequent dividend growth is very weak in the literature. Additionally, the poor out-of-sample performance does not simply mean that returns are unpredictable. It is not hard to believe that returns are predictable and such predictions are not very useful for making real-time trading decisions.

A large number of empirical studies on stock return predictability using dividend–price ratios are based on the U.S. data. International evidence on this topic is relatively weak, especially New Zealand evidence. Raj and Thurston (1995) is probably the only paper that checked the predictive power of dividend–price ratios in the New Zealand stock market. However, the sample size was considerably small (monthly data from 1980 to 1993). Therefore, one of the main aims of this research is to bridge this gap and investigate the predictive power of dividend–price ratios in the New Zealand stock market using a much bigger sample and more robust methods.

Chapter 3 Theory and Empirical Methods

3.1 Theory

Campbell and Shiller (1988a) developed a return approximation that related current price to future dividends and returns. This approximation is as follows:

$$1 = (1 + R_{t+1})^{-1}(1 + R_{t+1}) = (1 + R_{t+1})^{-1}\frac{P_{t+1}+D_{t+1}}{P_t},$$

where R_t, P_t and D_t are the stock return, price and dividend growth at time t, respectively.

If we multiply both sides by $\frac{\mathrm{P_t}}{\mathrm{D_t}}$, then the inverted dividend-price ratio can be written as:

$$\frac{\mathrm{P_t}}{\mathrm{D_t}} = (1 + \mathrm{R_{t+1}})^{-1}\frac{\mathrm{D_{t+1}}}{\mathrm{D_t}}\left(1 + \frac{\mathrm{P_{t+1}}}{\mathrm{D_{t+1}}}\right) .$$

Taking logs, with lowercase letters denoting the logs of uppercase letters, the log of the dividend–price ratio can be expressed as:

$$\ln\left(\frac{D_t}{P_t}\right) = d_t - p_t = r_{t+1} - \Delta d_{t+1} - \ln(1 + e^{p_{t+1}-d_{t+1}}),$$

where r_t is the continuously compounded stock return over period t and Δd_{t+1} is the dividend growth ($\Delta d_{t+1} = d_{t+1} - d_t$). We can approximate the last term of above equation with the first-order Taylor expansion with $\overline{\mathrm{P/D}} = e^{\overline{p-d}}$ as follows:

$$\ln(1 + e^{p_{t+1}-d_{t+1}}) \approx \ln(1 + \overline{\mathrm{P/D}}) + \frac{\overline{\mathrm{P/D}}}{1+\overline{\mathrm{P/D}}}[(p_{t+1} - d_{t+1}) - (\overline{p - d})].$$

Let $k = \ln(1+\overline{\mathrm{P/D}}) - \frac{\overline{\mathrm{P/D}}}{1+\overline{\mathrm{P/D}}}(\overline{p-d})$and $\rho = \frac{e^{E(p-d)}}{1+e^{E(p-d)}}$,. Therefore, the log of the dividend–price ratio can be approximated as:

$$d_t - p_t \approx r_{t+1} - \Delta d_{t+1} - k + \rho(d_{t+1} - p_{t+1}). \tag{1}$$

Equation (1) is the Campbell and Shiller (1998a) approximate present value identity. Solving Equation (1) forward, the approximate present value identity is expressed as:

$$d_t - p_t \approx -c + \sum_{j=1}^{k} \rho^{j-1}\left(r_{t+j} - \Delta d_{t+j}\right) + \lim_{j\to\infty} \rho^{j}\,(d_{t+j} - p_{t+j}). \tag{2}$$

Equation (2) implies that:

$$Var(d_t - p_t) \approx cov\left(d_t - p_t, \sum_{j=1}^{k} \rho^{j-1} r_{t+j}\right) - cov\left(d_t - p_t, \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}\right)$$

$$+\rho^k cov(d_t - p_t, d_{t+k} - p_{t+k}). \tag{3}$$

Equation (3) says that dividend–price ratios can only vary if they predict future returns, if they predict future dividend growth or if prices grow forever ("rational bubbles"). Dividing both sides of Equation (3) by $Var(d_t - p_t)$, we have:

$$1 \approx b_r^k - b_{\Delta d}^k + \rho^k b_{d-p}^k, \tag{4}$$

where b_r^k is the coefficient from a regression of weighted k-period future returns $(\sum_{j=1}^{k} \rho^{j-1} r_{t+j})$ on the current log dividend–price ratio $(d_t - p_t)$;

$b_{\Delta d}^{k}$ and b_{d-p}^{k} are defined similarly. b_{r}^{k}, $b_{\Delta d}^{k}$ and $\rho^{k} b_{d-p}^{k}$ can be read as the fractions of dividend–price variation attributed to time-varying expected returns, time varying expected dividend growth and dividend–price ratio persistence ("rational bubbles").

3.2 Empirical Methods

To examine the predictive power of dividend–price ratios in the New Zealand stock market, I have implemented the method introduced by Cochrane (2008), which uses both the direct approach and the first-order VAR approach. The difference between the two methods is that the long-horizon coefficients for the direct regressions might differ from the implied VAR coefficients when the first-order VAR model does not adequately capture a multi-period data-generating process for returns, dividend growth and dividend–price ratios. For example, if there is a shock in the current dividend yield and this shock has a long-lasting effect on future returns or dividend growth, the direct approach might give more correct estimates of the long-horizon coefficients than the first-order VAR approach. This is because the first-order VAR model might fail to capture the long-lasting effect due to the restrictions imposed in the model. On the other hand, the first-order VAR approach might have better finite sample properties and thus it gives higher power against the null hypothesis of no predictability. In short, as in Maio and Santa-Clara (2013) argued, there might be a trade-off between the two approaches.

The direct approach estimates below several regressions: the future log real returns and log dividend growth on the current dividend–price ratio at different time horizons, *k*:

$$\sum_{j=1}^{k} r_{t+j} = c_r + b_r^k (d_t - p_t) + \varepsilon_{t+k}^{r}; \tag{5}$$

$$\sum_{j=1}^{k} \Delta d_{t+j} = c_d + b_d^k (d_t - p_t) + \varepsilon_{t+k}^{d}; \tag{6}$$

$$\sum_{j=1}^{k} \rho^{j-1} r_{t+j} = c_{rw} + b_{rw}^k (d_t - p_t) + \varepsilon_{t+k}^{rw}; \tag{7}$$

$$\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} = c_{dw} + b_{dw}^k (d_t - p_t) + \varepsilon_{t+k}^{dw}. \tag{8}$$

In Equations (5) and (6), returns are unweighted, but in Equations (7) and (8), returns are weighted.[4] $\sum_{j=1}^{k} r_{t+j}$ and $\sum_{j=1}^{k} \Delta d_{t+j}$ denote the unweighted sum of single-period log real returns and log real dividend growth from period *t* to *t+k;* $\sum_{j=1}^{k} \rho^{j-1} r_{t+j}$ and $\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}$ denote the weighted sum of single-period log real returns and log real dividend growth from period *t* to *t+ k* (with a constant approximation of weighted $\rho = \frac{e^{E(p-d)}}{1+e^{E(p-d)}}$=0.949 in the data). For the horizon *k* of above 1 year, the use of overlapping data means the error terms to have a moving average structure of *k-1.* Therefore, the Newey–West adjusted standard errors with *k-1* lags are used to produce more accurate test statistics. Although there are various methods to calculate standard errors in the literature, the Newey–West adjusted and Hodrick standard errors are the most

[4]Many studies in the literature use unweighted returns and dividend growth when examining the predictive power of the dividend–price ratio for simplicity reasons. But according to the approximate present value identity in Equation (1), r_{t+j} and Δd_{t+j} should be weighted by ρ^{j-1}. This research reports the results using both weighted and unweighted returns and dividend growth.

widely used. However, there is no clear evidence as to which is superior to the other. To make the results simple to understand and easy to discuss, this thesis only reports the Newey–West adjusted standard errors (NW standard errors).

The VAR approach uses first-order VAR representations of log real returns, log real dividend growth, and log dividend–price ratio persistence. If we consider regressions of weighted returns and dividend growth on the dividend–price ratio, the first-order VAR system can be written as:

$$r_{t+1} = c_{rw} + b_{rw}(d_t - p_t) + \varepsilon_{t+1}^{rw}; \tag{9}$$

$$\Delta d_{t+1} = c_{dw} + b_{dw}(d_t - p_t) + \varepsilon_{t+1}^{dw}; \tag{10}$$

$$d_{t+1} - p_{t+1} = c_{d-p} + b_{d-p}(d_t - p_t) + \varepsilon_{t+1}^{d-p}. \tag{11}$$

Equations (9) and (10) are the return and dividend growth regressions. They are equivalent to Equations(5) to (8) for *k*=1. In other words, regression Equations(5) to (10) produce the same results for the 1-year regressions.

The implied long-horizon weighted coefficients for returns, dividend growth and the dividend–price ratio can be calculated from VAR system above as:[5]

$$b_i^k = \sum_{j=1}^{k} \rho^{j-1} \emptyset^{j-1} b_i = b_i \frac{1-(\rho\emptyset)^k}{1-\rho\emptyset}$$

$$b_{d-p}^k = (\rho\emptyset)^k,$$

where $i = r_w, d_w.$ and b_{d-p}^k is the long-horizon weighted coefficients for the dividend–price ratio, and $\emptyset = b_{d-p}^1$ is the log dividend–price ratio

[5]For the details of how the long-horizon coefficients are derived from short-horizon coefficients, please see Cochrane (2008). For a even better version of this, please see Cochrane (2014).

autocorrelation (estimated to be $\widehat{\emptyset} \approx 0.81$ in the data).

When *k* approaches infinity, the long-run weighted coefficients can be written as $b_{i,k} = \frac{b_i}{1-\rho\emptyset}$.

Similarly, the implied long-run unweighted coefficients can be calculated as:

$$b_i^k = \sum_{j=1}^{k} \emptyset^{j-1} b_i = b_i \frac{1-\emptyset^k}{1-\emptyset}$$

$$b_{d-p}^k = \emptyset^k$$

and the long-run unweighted coefficient is $b_{i,k} = \frac{b_i}{1-\emptyset}$.

In the infinite horizon decomposition, all the variation in the current dividend–price ratio is associated with either return or dividend growth because the predictability of the future dividend–price ratio vanishes out for a very long horizon:

$$Var(d_t - p_t) \approx cov\left(d_t - p_t, \textstyle\sum_{j=1}^{k} \rho^{j-1} r_{t+j}\right) - cov\left(d_t - p_t, \textstyle\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}\right),$$

therefore $1 = b_r^{\infty} - b_d^{\infty}$.

The *t*-statistics of the implied long-run coefficients are calculated based on the standard error of the single-period VAR coefficients using the Delta method (see Appendix A for details).

3.3 Excess Return Predictability

This research also assesses the predictive power of excess returns as the aggregate equity premium has also been the focus of the predictability research.

To investigate the excess return predictability, let $r_{t+j} = rf_{t+j} + rp_{t+j}$; ,where rf_{t+j} and rp_{t+j} are the risk-free rate and risk premium at time $t+j$. Therefore, the approximate present value identity can be written as:

$$d_t - p_t \approx -c + \sum_{j=1}^{k} \rho^{j-1} \left(rf_{t+j} + rp_{t+j} - \Delta d_{t+j} \right) + \lim_{j \to \infty} \rho^j \left(d_{t+j} - p_{t+j} \right)$$

Rearranging the above equation, we have:

$$d_t - p_t \approx -c + \sum_{j=1}^{k} \rho^{j-1} rp_{t+j} - \sum_{j=1}^{k} \rho^{j-1} \left(\Delta d_{t+j} - rf_{t+j} \right) + \lim_{j \to \infty} \rho^j \left(d_{t+j} - p_{t+j} \right). \tag{12}$$

The third term $\left(\left(\sum_{j=1}^{k} \rho^{j-1} \left(\Delta d_{t+j} - rf_{t+j} \right)\right)\right)$ in Equation (12) can be read as excess dividend growth. Therefore, the variance decomposition of Equation (12) is:

$$Var(d_t - p_t) \approx cov\left(d_t - p_t, \sum_{j=1}^{k} \rho^{j-1} rp_{t+j} \right) - cov\left(d_t - p_t, \sum_{j=1}^{k} \rho^{j-1} \Delta ed_{t+j} \right) + \rho^k cov(d_t - p_t, d_{t+k} - p_{t+k}). \tag{13}$$

Notice that in Equation (13), excess return predictability is associated with excess dividend growth predictability. Therefore, we can also examine the predictive power for excess returns and excess dividend growth using the direct approach and the VAR approach discussed in Section 3.2 (by replacing return and dividend growth in Equations (5)–(10) with excess return and excess dividend growth).

Chapter 4 Data

Annual observations of the value-weighted New Zealand stock index from 1931 to 2012 are used in this research. Annual data on stock market returns, bond yields, dividend–price ratios and dividend growth between 1931 and 2002 come from Lally and Marsden (2004), and were generously provided by Martin Lally. The rest of the stock market data are updated to 2012 using the information available from the NZX Company Research database;[6] bond and inflation data have been taken from the Reserve Bank of New Zealand's database.[7] A more detailed description of the construction of the data series is contained in Appendix B.

Instead of using the total bond returns, the annual actual bond yields are used as a proxy for the riskless rates. This is because of restrictions on the data: only 10-year New Zealand government bond data were available for this study.[8] The bond yields measure the holding period return if the bond is held to its maturity. Note that the bond yield for each year will be different from the actual bond return for each year, as bond returns change with changes in prices and coupons paid during the holding period.

However, the bond yields may not be an accurate measure of the riskless rate because yields might change for each holding period before the maturity date.

[6] Available athttp://companyresearch.nzx.com/crust/services.php
[7] Available athttp://www.rbnz.govt.nz/statistics/tables/b2/
[8] The 10-year bond is the only New Zealand government bond to exist for the entire 1931–2012 period.

This leads to a reinvestment risk on the coupon payments. Therefore, this proxy of riskless rates is very likely to be higher than true riskless rates.

When calculating excess returns, 1-year excess returns are calculated as the stock return of the year less the beginning-of-the-year yield of the 10-year government bond: $er_t = r_t - y_t$, where er_t and r_t are the excess returns and the actual stock returns, respectively, in year t; y_t is the bond yield at the beginning of year t.

The excess return proxy is likely to be noisy when the beginning-of-the-year yield of the 10-year government bond is used. For this reason, I will consider another method, which calculates the excess return series under the assumption that the 10-year government bond is identical to a perpetuity. To be more specific, let the bond return between t and $t+1$ be $y_t + \frac{y_t - y_{t+1}}{y_t}$, where y_t is the bond yield at the beginning of year t. The excess returns are then calculated as $erp_t = r_t - y_t + \frac{y_t - y_{t+1}}{y_t}$.

Table 1 below shows the descriptive statistics for the series. The average of log real return and log excess return are 4.7%, and 3.3% or 3.8% (depending on which method is used to calculate excess returns); the average dividend-price ratio is 5.5%. By comparison, the averages of real return, excess return and dividend yield for the New Zealand market calculated by Lally and Marsden (2004) for the period 1931–2002 are 4.7%, 2.9% and 5.1%, respectively. However, the periods studied are different. Dividend growth is about –1% on average and it is almost as variable as returns (or excess returns) in the sample period. Compared to the U.S. historical average, New Zealand's real return, excess return and dividend growth are higher, but dividend yield is lower. The historical average of real return, excess return, dividend growth and dividend yield in the U.S. are 7.4%, 4.9%, 4% and 3.6%, respectively.[9]

Table 1:Descriptive Statistics for the full sample (1931–2012)

Variable	Mean	Standard deviation	Min	Max	Number of positive observations	Number of negative observations
r	0.047	0.205	-0.756	0.750	54	27
er	0.033	0.201	-0.817	0.665	50	31
erp	0.038	0.218	-0.855	0.621	47	34
Δd	-0.010	0.172	-0.589	0.722	39	42
DP	0.055	0.014	0.029	0.088	81	0

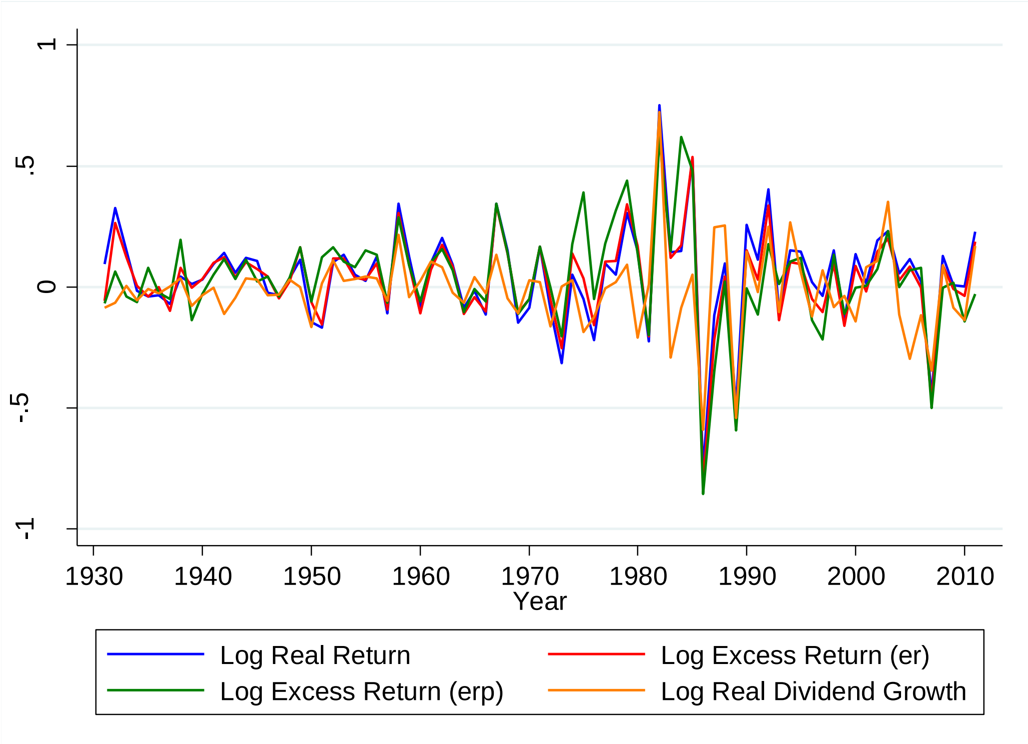
r isthe log of real annual stock index returns. er is the log real annual excess returns assuming that the riskless bond 1-year return equals its beginning-of-period yield.erp is the log of real annual excess returns assuming that the riskless bond is a perpetuity. Δd is the annual change in log dividends. DP is the nominal dividend–price ratio.

The time series of log real returns, log excess returns (both er and erp) and log real dividend growth are plotted in Figure 1a. During the sample period, real returns, excess returns and real dividend growth moved up and down in a similar fashion. The most volatile period in the data is the 1980s. Following the

[9]Average real return and excess return figures from the U.S. have been retrieved from Ibbotson Associates (2006) and the sample period is 1926–2005. Average dividend growth and dividend yield figures in the U.S. have been retrieved from Maio and Santa-Clara (2013), and the sample period is 1928–2010.

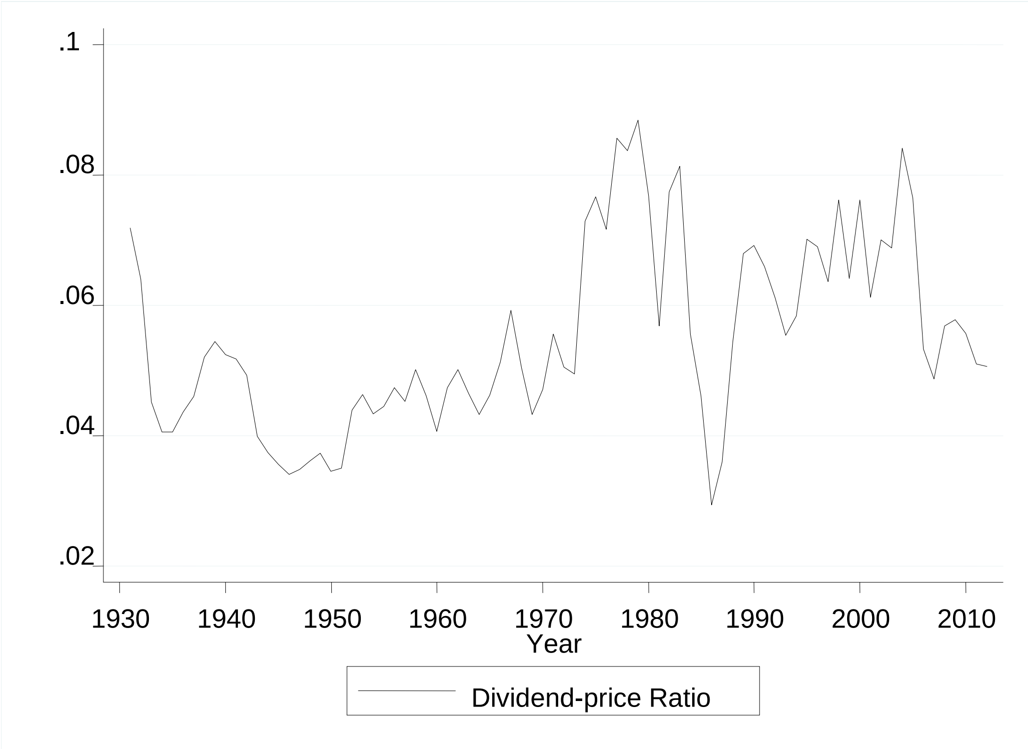
international bull market which began in 1982, the New Zealand stock market experienced its greatest rise in history. Not surprisingly, real returns, excess returns and real dividend growth reached their highest values (75%, 66.5% or 62.1% and 72.2%, respectively) in 1983. However, 4 years later, the New Zealand stock market suffered its biggest collapse: just one day after the dramatic fall of the U.S. stock market in October 19th, 1987, the New Zealand stock market collapsed. Real return, excess return and real dividend growth dropped to their lowest values in the sample (–75.6%, –81.7% or –85.5% and –58.9%, respectively). Furthermore, although minor differences between the two sets of excess return series (i.e., between *er* and *erp*) can be observed, they are considerably close, particularly after 1980.

Figure 1a: Time series of log real returns, log excess returns and log real dividend growth



The time series of the dividend–price ratio is plotted in Figure 1b. Apart from the first two years (1931 and 1932), dividend–price ratios were lower in the early part of the sample period and slowly increased after the 1960s. The most volatile period was the late 1970s to the late 1980s. The dividend–price ratio reached its highest value of 8.8% in 1979. During the New Zealand financial sector reform period, the dividend–price ratio dropped from 8.1% in 1983 to 5.6% in 1984. In 1986, the dividend–price ratio dropped to its lowest value of 2.9%. After that, it slowly recovered and researched its second highest value of 8.4% in 2004. However, during the global financial crisis in 2007, the dividend–price ratio dropped significantly to 4.8% and it has remained at this level since then.

Figure 1b: Time series of the dividend–price ratio



Chapter 5 Results

To examine the predictability in the New Zealand stock market and compare the results with the existing research, this chapter uses the full 1931–2012 sample to estimate return and dividend growth coefficients under both the direct and VAR-implied approach for different time horizons(k). Section 5.1 reports the weighted regression results; Section 5.2 provides the unweighted regression results.

5.1 Weighted Regressions

Table 2 reports the weighted coefficient estimates from Equations (5) and (6) under the direct approach for $k =$ 1, 3, 5, 10 and 15. From Panel A in Table 2, we can see that there is clear evidence of stock real return predictability for short (1 year), medium (3 to 5 year) and long horizons (10 year and above) in the New Zealand stock market. The estimates of real return predictability coefficients are both economically large and statistically significant for all values of k using the NW standard errors (discussed in Chapter 3). At the 1-year horizon, the direct approach suggests that expected return volatility accounts for about 27% of the variation in the dividend–price ratio, increasing to 53%, 64% and 70% over 3, 5 and 10 years, respectively. At the 15-year horizon, the coefficient decreases to 0.67. The reason why the 15-year return coefficient falls is possibly due to the small sample size. As more of the overlapping data are used, the sample size becomes relatively small for the 15-year regressions, which can potentially introduce noise to the model. The R^2 values are high and they increase with the horizon. Increases in the coefficients and R^2 values imply that the predictive power of the dividend–price ratio for real returns increases with the horizon. Compared with Cochrane's finding (Cochrane 2008, Table 6) for real returns in the U.S., the direct return point estimates are about two times higher at 1- to 5-year horizons. For horizons above 5 years, real return point estimates are lower than what Cochrane found for the U.S. (20–60% lower, depending on the horizon).

Table 2: Direct weighted regressions: full sample (1931–2012)

	k	Constant	Coefficient	NW standard error	t-statistic	p-value	R^2
Panel A r	1	0.83	0.27	0.08	3.22	0.00	0.12
	3	1.68	0.53	0.17	3.19	0.00	0.22
	5	2.09	0.64	0.20	3.28	0.00	0.22
	10	2.42	0.70	0.18	3.80	0.00	0.31
	15	2.48	0.67	0.20	3.38	0.00	0.32
Panel B er	1	0.74	0.24	0.08	2.91	0.00	0.10
	3	1.47	0.47	0.19	2.47	0.02	0.18
	5	1.73	0.54	0.26	2.06	0.04	0.15
	10	1.59	0.45	0.29	1.55	0.13	0.12
	15	1.26	0.30	0.24	1.25	0.22	0.05
Panel C erp	1	0.78	0.25	0.09	2.80	0.00	0.09
	3	1.57	0.50	0.27	1.81	0.08	0.12
	5	1.88	0.58	0.41	1.39	0.17	0.10
	10	1.38	0.34	0.58	0.58	0.57	0.02
	15	0.67	0.04	0.49	0.09	0.93	0.00
Panel D Δd	1	0.09	0.03	0.07	0.46	0.65	0.00
	3	-0.26	-0.08	0.11	-0.72	0.47	0.01
	5	-0.24	-0.07	0.16	-0.42	0.68	0.00
	10	-0.66	-0.21	0.13	-1.63	0.11	0.05
	15	-0.74	-0.23	0.19	-1.25	0.22	0.06
Panel E Δed	1	-0.01	0.01	0.07	0.08	0.94	0.00
	3	-0.47	-0.14	0.13	-1.05	0.30	0.03
	5	-0.60	-0.17	0.22	-0.79	0.44	0.03
	10	-1.49	-0.46	0.22	-2.12	0.04	0.17
	15	-1.95	-0.61	0.23	-2.61	0.01	0.22
Panel F Δedp	1	0.03	0.02	0.09	0.20	0.84	0.00
	3	-0.38	-0.12	0.23	-0.50	0.62	0.01
	5	-0.44	-0.13	0.37	-0.36	0.72	0.01
	10	-1.70	-0.57	0.51	-1.12	0.27	0.07
	15	-2.55	-0.86	0.48	-1.78	0.08	0.11

Predictability coefficient estimates for the weighted direct approach from 1931 to 2012. r is the log real return, er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Panels B and C in Table 2 show some evidence for excess return predictability. However, unlike Cochrane (2008), who found stronger return predictability for excess returns, the point estimates and R^2 values for excess returns in Panels B and C are all smaller than their real return counterparts. Furthermore, the coefficients are generally insignificant at long horizons. This decrease in predictive power for excess returns is almost certainly due to the noise in the bond return series, as discussed in Chapter 4. It seems that calculating excess returns with the assumption that the 10-year government bond is identical to a perpetuity does not solve the noise in the bond return series. Even though the bond series is noisy, we can still see some predictive power for excess returns at short to medium horizons (1 to 3 years in Panels B and C).

Panel D provides evidence to confirm that real dividend growth is not predictable. The real dividend growth coefficients are not statistically significant. Additionally, the R^2 values are weak. Only the 10-year real dividend growth coefficient is close to being significant (p-value= 0.11) but the R^2 is only 5% in this case. Panels E and F show that excess dividend growth is generally not predictable. The only exceptions are in Panel E, where dividend growth becomes predictable at 10-year and 15-year horizons. However, this could be due to the noise in the bond return series as well.

Table 3 shows the weighted coefficient estimates from the VAR-implied approach for $k =$ 1, 3, 5, 10, 15 and ∞.In Panel A, the implied estimates for real return are higher than the direct estimates. Expected real returns variation accounts for 27%, 63%, 84%, 107% and 112% of dividend–price ratio volatility for $k =$ 1, 3, 5, 10, and 15. At longer horizons, 115% of dividend yield volatility is associated with the expected real return variation. The VAR approach also gives larger t-statistics to real return estimates compared with the direct approach. When we look at excess return predictability, the VAR approach gives a different picture. While the direct approach suggests that excess return is not predictable at long horizons, the VAR approach suggests otherwise. From Panels B and C, we can see that excess return estimates are all economically large and statistically significant at all horizons. The predictive power also increases with the time horizon. However, the return predictability of excess returns is still not stronger than their real return counterparts such as Cochrane (2008) found under the VAR approach. This could still be due to the noise in the bond return series. In Panels D, E and F, we can see that real and excess dividend growth are nowhere near being predictable under the VAR approach. The coefficients are all very small with incorrect signs and are also statistically insignificant.

Table 3: VAR-implied weighted regressions: full sample (1931–2012)

	k	Coefficient	NW standard error	*t*-statistic	*p*-value
	1	0.27	0.08	3.22	0.00
	3	0.63	0.18	3.53	0.00
Panel A	5	0.84	0.23	3.70	0.00
r	10	1.07	0.29	3.69	0.00
	15	1.12	0.31	3.58	0.00
	∞	1.15	0.33	3.42	0.00
	1	0.24	0.08	2.91	0.00
	3	0.56	0.18	3.17	0.00
Panel B	5	0.75	0.23	3.31	0.00
er	10	0.95	0.28	3.36	0.00
	15	1.01	0.31	3.29	0.00
	∞	1.02	0.32	3.19	0.00
	1	0.25	0.09	2.80	0.00
	3	0.59	0.20	2.97	0.00
Panel C	5	0.79	0.26	3.04	0.00
erp	10	1.00	0.33	3.00	0.00
	15	1.06	0.36	2.92	0.00
	∞	1.08	0.38	2.82	0.01
	1	0.03	0.07	0.46	0.65
Panel D	3	0.08	0.18	0.46	0.65
Δd	5	0.11	0.24	0.45	0.65
	10	0.14	0.30	0.45	0.66
	15	0.14	0.32	0.44	0.66
	∞	0.15	0.33	0.44	0.66
	1	0.01	0.07	0.08	0.94
Panel E	3	0.01	0.17	0.08	0.94
Δed	5	0.02	0.23	0.08	0.94
	10	0.02	0.29	0.08	0.94
	15	0.02	0.31	0.08	0.94
	∞	0.02	0.32	0.08	0.94
	1	0.02	0.09	0.20	0.84
	3	0.04	0.20	0.20	0.84
Panel F	5	0.06	0.27	0.20	0.84
Δedp	10	0.07	0.35	0.20	0.84
	15	0.07	0.37	0.20	0.84
	∞	0.08	0.38	0.20	0.84

Predictability coefficient estimates for the weighted VAR approach from 1931 to2012. r is the log real return,er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

By comparing Tables 2 and 3, we see that the results are relatively similar in the sense that under both the direct and VAR-implied approaches, expected return variation accounts for most of the dividend–price ratio volatility, and expected dividend growth variation accounts for almost no dividend–price ratio volatility. In other words, return predictability is the main driver of the variation in the dividend–price ratios in the New Zealand stock market, not dividend growth predictability.

5.2 Unweighted regression

Tables 4 and 5 report the unweighted regression results. By comparing Tables 2 and 3 to Tables 4 and 5, we can see that the main conclusions are insensitive to the choice between weighted and unweighted regressions. Since the weight $\rho = 0.949$, which is close to 1 in the New Zealand data, this conclusion is not surprising. However, direct weighted return and excess return regressions produce higher *t*-statistics and R^2 values compared with unweighted regressions in most cases. The implied weighted return and excess return regressions also produce higher *t*-statistics at long horizons compared with the unweighted regressions. This suggests that weighted regressions seem to have a little more power to detect predictability.

Table 4: Direct unweighted regressions: full sample (1931–2012)

	k	Constant	Coefficient	NW standard error	t-statistic	p-value	R^2
Panel A r	1	0.83	0.27	0.08	3.22	0.00	0.12
	3	1.75	0.55	0.17	3.17	0.00	0.21
	5	2.23	0.68	0.21	3.21	0.00	0.21
	10	2.55	0.71	0.24	3.01	0.00	0.22
	15	2.62	0.65	0.25	2.59	0.00	0.18
Panel B er	1	0.74	0.24	0.08	2.91	0.00	0.10
	3	1.53	0.49	0.20	2.46	0.02	0.17
	5	1.83	0.57	0.29	1.99	0.05	0.14
	10	1.47	0.38	0.33	1.15	0.26	0.06
	15	0.71	0.07	0.25	0.27	0.79	0.00
Panel C erp	1	0.78	0.25	0.09	2.80	0.00	0.09
	3	1.63	0.51	0.29	1.78	0.08	0.12
	5	2.00	0.61	0.45	1.34	0.18	0.09
	10	1.04	0.19	0.67	0.29	0.78	0.00
	15	-0.58	-0.45	0.48	-0.94	0.35	0.02
Panel D Δd	1	0.09	0.03	0.07	0.46	0.65	0.00
	3	-0.28	-0.09	0.12	-0.74	0.46	0.01
	5	-0.26	-0.07	0.18	-0.40	0.69	0.00
	10	0.07	-0.31	0.16	-1.94	0.06	0.07
	15	-0.12	-0.38	0.30	-1.27	0.21	0.08
Panel E Δed	1	-0.01	0.01	0.07	0.08	0.94	0.00
	3	-0.51	-0.15	0.14	-1.07	0.29	0.03
	5	-0.66	-0.19	0.24	-0.77	0.44	0.03
	10	-2.13	-0.66	0.26	-2.59	0.01	0.22
	15	-3.11	-0.97	0.30	-3.25	0.00	0.28
Panel F Δedp	1	0.03	0.02	0.09	0.20	0.84	0.00
	3	-0.41	-0.13	0.24	-0.52	0.60	0.01
	5	-0.49	-0.15	0.41	-0.36	0.72	0.01
	10	-2.55	-0.85	0.59	-1.44	0.15	0.10
	15	-4.41	-1.49	0.54	-2.76	0.01	0.17

Predictability coefficient estimates for the direct unweighted approach from 1931 to 2012. r is the log real return, er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Table 5: VAR-implied unweighted regressions: full sample (1931–2012)

	k	Coefficient	NW Standard error	*t*-statistic	*p*-value
Panel A *r*	1	0.27	0.08	3.22	0.00
	3	0.66	0.19	3.55	0.00
	5	0.91	0.25	3.71	0.00
	10	1.23	0.34	3.62	0.00
	15	1.33	0.39	3.38	0.00
	∞	1.39	0.45	3.12	0.00
Panel B *er*	1	0.24	0.08	2.91	0.00
	3	0.59	0.19	3.18	0.00
	5	0.82	0.25	3.33	0.00
	10	1.10	0.33	3.32	0.00
	15	1.19	0.38	3.16	0.00
	∞	1.24	0.42	2.97	0.00
Panel C *erp*	1	0.25	0.09	2.80	0.00
	3	0.62	0.21	2.98	0.00
	5	0.86	0.28	3.05	0.00
	10	1.15	0.39	2.94	0.00
	15	1.25	0.45	2.79	0.01
	∞	1.31	0.50	2.62	0.01
Panel D Δd	1	0.03	0.07	0.46	0.65
	3	0.08	0.18	0.46	0.65
	5	0.12	0.26	0.45	0.65
	10	0.16	0.35	0.45	0.66
	15	0.17	0.38	0.44	0.66
	∞	0.18	0.40	0.44	0.66
Panel E Δed	1	0.01	0.07	0.08	0.94
	3	0.01	0.18	0.08	0.94
	5	0.02	0.25	0.08	0.94
	10	0.03	0.34	0.08	0.94
	15	0.03	0.37	0.08	0.94
	∞	0.03	0.38	0.08	0.94
Panel F Δedp	1	0.02	0.09	0.20	0.84
	3	0.04	0.21	0.20	0.84
	5	0.06	0.30	0.20	0.84
	10	0.08	0.40	0.20	0.84
	15	0.09	0.44	0.20	0.84
	∞	0.09	0.46	0.20	0.84

Predictability coefficient estimates for the weighted VAR approach from 1931 to 2012. r is the log real return, er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Chapter 6 Risk-pricing or Mispricing?

In the previous chapter, I have found New Zealand evidence that the dividend–price ratio has strong predictive power for future returns. However, is this observed predictive power associated with risk-pricing or mispricing? On one hand, a high dividend–price ratio may be a signal of high future risk. Therefore, the expected returns have to be adjusted to match up with the high future risk. As a result, any subsequent average returns will also be high and this produces the predictability we see. On the other hand, a high dividend–price ratio could also mean that stock prices are low relative to their intrinsic values. As investors realise that stocks are mispriced, prices will increase and therefore, the subsequent returns will be high.

The New Zealand stock market provides a good background to allow me to test whether the return predictability is associated with risk-pricing or mispricing. Before July 1984, the New Zealand stock market was considered to be highly regulated. For example, the exchange rate was fixed and entry to the foreign exchange market was very difficult: private overseas borrowing, foreign-owned companies, access to domestic financial markets and the ability of New Zealand residents to buy foreign exchange for investment purposes were all highly restricted. There were also many restrictions on financial institutions, such as official and unofficial short-term money market dealers, finance and trust companies, stock agents and private mortgage lenders. All these restricted information being incorporated in stock prices; therefore, the degree of mispricing in the pre-reform period seems to be considerably high. Groenewold (1997) reports evidence that supports this idea (although this evidence is not very strong).

Since July 1984, liberalisation has helped the New Zealand financial market become an extremely open market with a few distortions and open entry. The exchange rate has been floated; the foreign exchange trading restrictions have been removed; borrowing and lending have become much easier because of the removal of liquidity ratios on all financial institutions; the interest rate, which was fully regulated, has become market-determined; and the entry and exit of banks have become free. After market liberalisation, the information can be more easily incorporated into stock prices; therefore the degree of mispricing seems to be low in the post-reform period.

If mispricing is the main driver of the observed predictability in New Zealand, then we should see a stronger relationship between dividend–price ratios and future stock returns in the pre-reform period because the degree of mispricing is considerably high. We should also see a weaker relationship in the post-reform period, as the mispricing opportunities would seem to be less. On the other hand, if risk-pricing is the main driver of the observed predictability, any change that increases or decreases mispricing would have no effect on the relationship between dividend-price ratios and future stock returns. In other words, the relationship between dividend-price ratios and future stock returns would be about the same in the pre-reform and post-reform periods.

To explain the risk-pricing and mispricing hypotheses more clearly in mathematical terms, let b_r^k denote the return predictability, and $\bar{r}$ and z denote the expected return associated with the risk-pricing and mispricing components respectively. Now $b_r^k = b_{\bar{r}}^k + b_z^k$ (i.e., the return predictability is due to risk-pricing $(b_{\bar{r}}^k)$ or mispricing (b_z^k)). If we hypothesise that the predictability is primarily due to mispricing, then we would expect a fall in b_z^k in the post-reform period, as mispricing was significantly reduced in this period. As a result, b_r^k will also fall. If we form a similar hypothesis about risk-pricing, a reduction in mispricing opportunities will not have any effect on $b_{\bar{r}}^k$. Therefore, b_r^k is expected to stay unchanged. It also could be the case that we might see a increase in $b_{\bar{r}}^k$ if the reform improves risk-pricing accuracy in the New Zealand market, which would lead to an increase in b_r^k.

To examine whether the observed return predictability is due to mispricing or risk-pricing, I compare the estimates of b_r^k from 1931–1984 and those from 1985–2012. For simplicity reasons, this chapter only reports the weighted regression for both the direct and VAR approach, as both the weighted and unweighted regressions give the same conclusions as those shown in Chapter 5. Furthermore, the results for direct regressions beyond a 5-year horizon are not reported because the sample size becomes very small for the post-reform period (18 observations for the 10-year regression; there are not enough observations to run the 15-year regressions).

If the observed predictability in the New Zealand stock market is primarily associated with mispricing, we should see a fall in the return coefficients in the post-reform sample. However, In Table 6, we can see this is not the case. At all horizons, the return and excess return coefficients are greater in the post-reform sample. Also, there are some cases where the post-reform coefficients are greater than the pre-reform coefficients at the 0.05 significance level following the Welch *t*-tests (Welch, 1947). In some cases, the post-reform coefficients are close to being significantly greater than the pre-reform coefficients. However, because there are only a small number of observations in the post-reform sample, this means that the Welch *t*-tests cannot reject the null hypothesis of there being no difference between the post-reform and pre-reform coefficients. The post-reform real and excess return coefficients are about two times larger than the pre-reform coefficients at 1-year to 3-year horizons; at a 5-year horizon, they are still 60%–70% larger. The difference only becomes small in the long run.

It is important to rule out the possibility that the increase in predictability began prior to 1984. To test this, I first divide the 1931–1984 data into two sub-periods and compare the return coefficients between these sub-periods. The first sub-period is 1931–1950 (20 observations) and the second sub-period is 1951–1984 (34 observations). Welch's *t*-test is then used to test whether the coefficient of the second sub-period is significantly greater than the coefficient of the first sub-period. Next, I continue to roll the first sub-period forward 1 year at a time until there are only 20 observations for the second sub-period. For example, the coefficient of 1931–1950 is compared with the coefficient of 1951–1984, then 1931–1951 with 1952–1984, through to a comparison of 1931–1964 with 1965–1984. The results (in Appendix C) show that the increase in return predictability does not occur prior to 1984. For real returns, the Welch's *t*-tests reject the null hypothesis of greater coefficients in the second sub-period at 1-, 3- and 5-year horizons for most cases. For excess returns, the results suggest that there is no significant difference between the two sub-periods in all cases.

Based on the mispricing hypothesis, we should see weaker return predictability in the post-reform sample. However, instead of weaker return predictability, we see that the return predictability is much stronger in the post-reform period. This suggests that the return predictability in the New Zealand stock market is not due to mispricing. If the return predictability is really due to mispricing, market liberalisation must have resulted in more mispricing and arbitrage opportunities in the market, or else market liberalisation has led to less mispricing and arbitrage opportunities, although this has created a longer-lasting mispricing. Both of these arguments are very unconvincing.

Table 6: Weighted regressions: 1931–1984 sample vs.1985–2012 sample

	k	Coefficient	NW standard error	t-stats	p-value	R^2
Panel A						
r	1	0.23	0.09	2.7	0.01	0.13
	3	0.50 (0.56)	0.21 (0.19)	2.41 (3.04)	0.02 (0.00)	0.21
	5	0.63 (0.77)	0.21 (0.24)	3.07 (3.25)	0.00 (0.00)	0.23
	∞	(1.11)	(0.34)	(3.10)	(0.00)	–
Panel B						
er	1	0.23	0.08	3.05	0.00	0.15
	3	0.51(0.56)	0.16(0.17)	3.19(3.38)	0.00(0.00)	0.32
	5	0.61(0.76)	0.19(0.22)	3.26(3.55)	0.00(0.00)	0.29
	∞	(1.10)	(0.36)	(3.02)	(0.00)	–
Panel C						
erp	1	0.30	0.08	3.59	0.00	0.20
	3	0.67(0.72)	0.21(0.18)	3.20(4.11)	0.00(0.00)	0.35
	5	0.78(0.98)	0.28(0.23)	2.81(3.36)	0.01(0.00)	0.31
	∞	(1.42)	(0.42)	(3.39)	(0.00)	–

1985–2012 post-reform sample

	k	Coefficient	NW standard error	t-stats	p-value	R^2
Panel E						
r	1	0.50	0.21	2.43	0.02	0.19
	3	1.01* (1.01)	0.18 (0.38)	5.58 (2.62)	0.00 (0.01)	0.48
	5	1.08 (1.20)	0.31 (0.47)	3.54 (2.54)	0.00 (0.01)	0.41
	∞	(1.32)	(0.59)	(2.24)	(0.03)	–
Panel F						
er	1	0.50	0.21	2.39	0.02	0.15
	3	1.07*(1.01)	0.18(0.39)	5.87(2.61)	0.00(0.01)	0.51
	5	1.25*(1.21)	0.31 (0.47)	4.06(2.55)	0.00(0.01)	0.50
	∞	(1.33)	(0.59)	(2.27)	(0.03)	–
Panel G						
erp	1	0.54	0.21	2.64	0.01	0.20
	3	1.17*(1.08)	0.18(0.38)	6.42(2.83)	0.00(0.01)	0.51
	5	1.60*(1.29)	0.29(0.48)	5.50(2.70)	0.00(0.01)	0.59
	∞	(1.43)	(0.61)	(2.33)	(0.02)	–

Predictability coefficient estimates are for both the direct approach and the VAR approach for the 1931–1984 and 1985–2004 samples. Weight, ρ=0.952; dividend–price ratio persistence for the 1931–1984 sample, $\emptyset = 0.828$. Weight, ρ=0.944; dividend–price ratio persistence for the 1985–2012 sample, $\emptyset = 0.657$.Numbers not in parentheses are estimates associated with the direct approach; numbers in parentheses are estimates associated with the VAR approach. r is the log real return, er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity.* indicates that the post-reform coefficient is greater than the pre-reform coefficient at the 0.05 significance level or better, based on Welch's t-test (Welch, 1947).

One major potential cause of the increase in return predictability in the post-reform period may be the result of the small sample size. The outlier effect will thus have a strong impact on the estimates in a small sample. There are two major financial crises within the post-reform sample: the Black Monday Crisis of 1987 and the Global Financial Crisis of 2008. When more data become available, we may see a fall in return predictability for the post-reform period, as the outlier effect will be reduced by an increase in the sample size.

Chapter 7 Fundamental Relationship or Historical Events?

Is the observed return predictability in New Zealand due to the fundamental relationship between the dividend–price ratio and future returns? Or is it due to something else? Cornell (2013) argues that there are two different ways to interpret return predictability evidence in the literature. The first interpretation is that the return predictability we see is due to the fundamental relationship between the dividend–price ratio and future returns. The second interpretation argues that this return predictability (mainly coming from the U.S. data) may be caused by a combination of different historical events. He indicates that when events such as the Great Depression, World War II, the Nifty-Fifty Stock Market Boom and the Dot-Com Bubble happened, investors would forecast the long-run impact of the events on dividend growth. However, the fact is that the real dividend growth rate (about 3.4% per annum) has almost never changed in the U.S. for almost over a century. When investors forecasted a higher or lower real dividend growth rate, they turned out to be wrong. When they realised their mistakes, prices had to adjust to bring dividend–price ratios back to match the revised expectations. This produced a correlation between the dividend–price ratio and subsequent returns. It might be the case that the return predictability we see in the U.S. is caused by this adjustment. In other words, investors have wrongly forecasted the long-run dividend growth and this caused dividend–price ratios to differ from their equilibrium values. Therefore, prices have had to adjust to bring the dividend–price ratios back to their equilibrium values. This interpretation seems to imply that investors were irrational and every time they tried to predict dividend growth, they turned out to be wrong. However, Cornell explains that this does not necessarily mean that investors were irrational. When events such as the Great Depression, World War II and the Nifty-Fifty Stock Market Boom happened, investors were actually rational and tried to predict future dividend growth based on how they evaluated the impacts of each event. However, the fact is that as far as dividend growth was concerned, these events did not change the constant dividend growth in the U.S.

Cornell (2013) provides a simple method to investigate the second interpretation. He explains that if the predictability is caused by the adjustments from the actual dividend–price ratios to their equilibrium values, then the explanatory power of return regressions such as Equations (5) and (7) discussed in Chapter 3 should increase if the difference between the actual and the equilibrium dividend–price ratio is used as the explanatory variable. He uses a linear trend to represent the equilibrium dividend–price ratios and finds that the explanatory power of return regressions has improved substantially for the U.S. data. However, dividend–price ratios are unrelated to future dividend growth. He concludes that the relationship between dividend–price ratio and future returns is an artefact of a certain combination of historical events in the U.S. This relationship produced the return predictability we see in the U.S. However, this relationship is unlikely to hold in the future because the unique historical events that happened in the past are very unlikely to repeat in the future.

To test whether the historical events are associated with the return predictability, I will follow Cornell's approach. I will use the upward trend (shown in Figure 2) in the New Zealand data to represent the equilibrium dividend–price ratios, and use the difference between the actual and the equilibrium dividend–price ratios as the explanatory variable. The direct regressions can be written as:

$$\sum_{j=1}^{k} r_{t+j} = c_r + b_r^k (d_t * -p_t *) + \varepsilon_{t+k}^{r}; \tag{14}$$

$$\sum_{j=1}^{k} \Delta d_{t+j} = c_d + b_d^k (d_t * -p_t *) + \varepsilon_{t+k}^{d}; \tag{15}$$

$$\sum_{j=1}^{k} \rho^{j-1} r_{t+j} = c_{rw} + b_{rw}^k (d_t * -p_t *) + \varepsilon_{t+k}^{rw}; \tag{16}$$

$$\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j} = c_{dw} + b_{dw}^k (d_t * -p_t *) + \varepsilon_{t+k}^{dw}. \tag{17}$$

The first-order VAR system can then be expressed as:

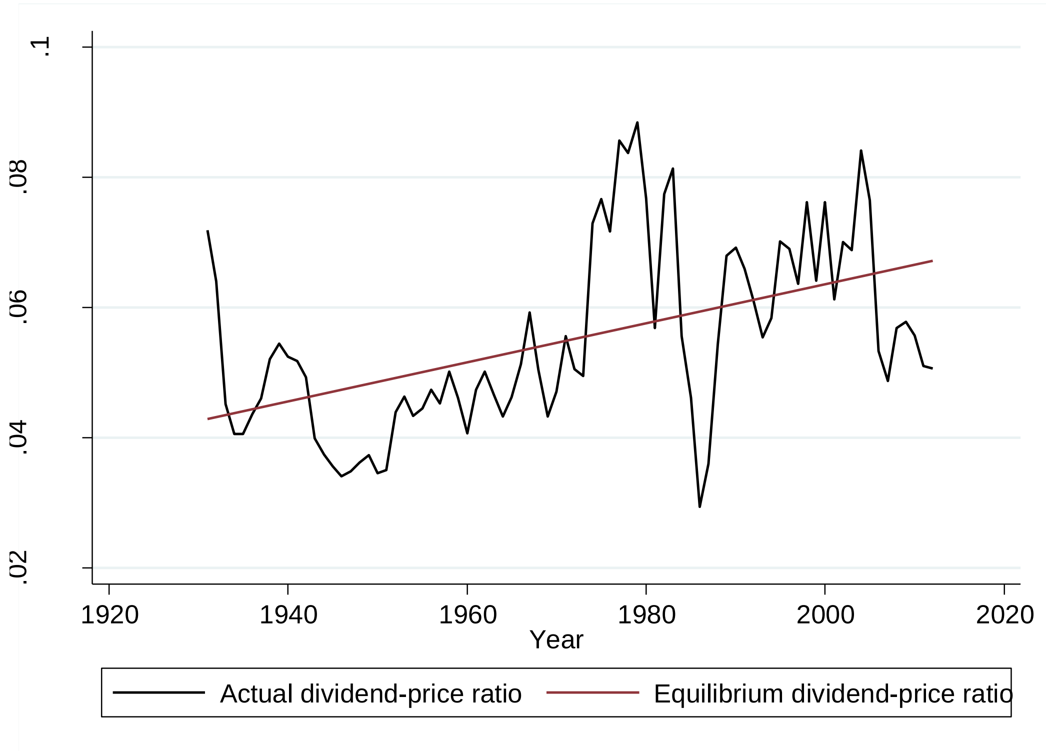
$$r_{t+1} = c_{rw} + b_{rw} (d_t * -p_t *) + \varepsilon_{t+1}^{rw}; \tag{18}$$

$$\Delta d_{t+1} = c_{dw} + b_{dw} (d_t * -p_t *) + \varepsilon_{t+1}^{dw}; \tag{19}$$

$$d_{t+1} - p_{t+1} = c_{d-p} + b_{d-p} (d_t * -p_t *) + \varepsilon_{t+1}^{d-p}, \tag{20}$$

where $(d_t * -p_t *)$ is the difference between the actual dividend–price ratio and the upward trend in Figure 2.

Figure 2 Actual and equilibrium dividend–price ratios, 1931–2012.



Tables 7 and 8 present the results for the weighted real and excess returns, and real and excess dividend growth regressions. The general conclusions in Table 7 and 8 remain the same as those reported in Table 2 and 3: real and excess returns are predictable, but real and excess dividend growth are not. The only exception is that the direct coefficient for the 10-year dividend growth regression in Table 7 Panel D is now significant at the 5% level, comparing this figure with the 10-year dividend growth regression in Table 2 Panel D, we can see that the difference is not very significant: the direct coefficient for the 10-year dividend growth regression in Table 2 is close to being significant at the 10% level (with a *p*-value of 0.11).

Under the direct approach, the coefficients, *t*-statistics and R^2 for the return and excess return regressions have substantially increased when *d*-p** is used as the explanatory variable. In Table 2, the best-case scenario is that expected return and excess return volatility only account for about 70% and 60% of the variation in the dividend–price ratio, respectively. However, in Table 7, we can see that the expected return and excess return volatility account for a large percentage of the variation (as large as 94% at most) of the adjustments from the actual dividend–price ratios to their equilibrium values. Under the implied approach (Table 8), we can also see a significant increase in predictability when *d*-p** is used as the explanatory variable. At the 3-year horizon, almost 90% of the expected return and excess return volatility is associated with the variation of the adjustments from the actual dividend–price ratios to their equilibrium values. The coefficients increase with the horizon: the expected return and excess return volatility account for 160% and 173% (or 157%, depending on which excess return series is used) of the variation in the adjustments from the actual dividend–price ratios to their equilibrium values at the long run.

Although the use of an upward trend to represent the equilibrium dividend–price ratio may not be a very accurate measurement of the true equilibrium, the results in Table 7 and 8 serve as a warning: a significant portion of the return predictability in the New Zealand stock market seems to be related with historical events. We therefore need to pay attention to the historical events that generate financial data in dividend–price ratios and return predictability research. This does not mean that there is no fundamental unchanging relationship between the variables, but this relationship seems to be overpowered by the effects of historical events.

The results in Table 7 and 8 also suggest some meaningful implications. Firstly, if the observed predictability is related to historical events, we might not see the same predictability patterns that we have seen in previous chapters. For example, at some point in the future, the impact of some events may overwhelm the fundamental relationship among returns, dividend growth and dividend yields. If this happens, the methods such as those used in this research might not detect any predictive power.

Secondly, the results in Table 7 and 8 indicate that data from different countries will produce different results because historical events are unique in each country. This conclusion is supported by Campbell (2003), Cornell (2014), Engsted and Pedersen (2010) and others. They found that there is strong evidence of return predictability in countries such as U.S., the U.K. and Australia. In countries such as Canada, France, Japan, the Netherlands, Sweden and Denmark, dividend growth is predictable but not returns.

Finally, the results suggest that we should pay attention to the impact of the historical events that generate our financial data. As Cornell (2013) argues:"*Every historical event is unique, so data generated by an historical process are potentially completely nonstationary. It is possible, of course, that* *nonstationary historical events produce stationary time series, but whether they do cannot be determined by examining the data alone without explicitly consider the historical events that generated it.*" In terms of valuation ratios and return predictability research, although it is not easy to account for the influence of historical events, Campbell and Shiller (1998) shed some light on the issue. They adjust the valuation ratios such as the dividend–price ratio and the price–earnings ratio on the basis of different financial policies and business cycles. For example, they calculated an adjusted price–earnings ratio by taking an index of stock market prices such as S&P 500 and dividing this by the average of the last 10 years of aggregate earnings. They then regressed the adjusted price–earnings ratio on the future stock returns and found that the adjusted price–earnings ratio had significant predictive power for stock returns.

Table 7: Weighted direct regressions using d^*-p^* as the explanatory variable

	k	Constant	Coefficient	NW standard error	t-stats	p-value	R^2
Panel A r	1	0.05	0.37	0.10	3.92	0.00	0.16
	3	0.12	0.76	0.18	4.22	0.00	0.32
	5	0.18	0.91	0.18	4.96	0.00	0.31
	10	0.36	0.86	0.20	4.40	0.00	0.34
	15	0.48	0.77	0.19	4.08	0.00	0.32
Panel B er	1	0.03	0.37	0.09	3.93	0.00	0.16
	3	0.09	0.78	0.21	3.81	0.00	0.35
	5	0.13	0.94	0.27	3.47	0.00	0.33
	10	0.27	0.82	0.30	2.77	0.01	0.29
	15	0.37	0.65	0.30	2.14	0.04	0.19
Panel C erp	1	0.04	0.40	0.10	4.00	0.00	0.17
	3	0.11	0.86	0.32	2.68	0.01	0.25
	5	0.18	1.07	0.46	2.31	0.02	0.23
	10	0.38	0.80	0.67	1.19	0.24	0.09
	15	0.54	0.48	0.67	0.73	0.47	0.03
Panel D Δd	1	-0.01	0.06	0.09	0.63	0.53	0.00
	3	-0.03	-0.06	0.10	-0.63	0.53	0.00
	5	-0.04	-0.02	0.15	-0.11	0.91	0.00
	10	-0.04	-0.28	0.13	-2.18	0.03	0.07
	15	-0.04	-0.29	0.21	-1.40	0.17	0.07
Panel E Δed	1	-0.02	0.05	0.09	0.56	0.58	0.00
	3	-0.06	-0.04	0.15	-0.28	0.78	0.00
	5	-0.10	0.01	0.25	0.05	0.96	0.00
	10	-0.13	-0.32	0.26	-1.23	0.22	0.06
	15	-0.15	-0.41	0.33	-1.23	0.22	0.08
Panel F Δedp	1	-0.02	0.08	0.10	0.84	0.41	0.01
	3	-0.04	0.03	0.30	0.11	0.92	0.00
	5	-0.05	0.14	0.47	0.30	0.77	0.00
	10	-0.02	-0.35	0.63	-0.55	0.58	0.02
	15	0.02	-0.57	0.69	-0.83	0.41	0.04

Predictability coefficients for estimates of d^*-p^*under the direct approach from the full 1931–2012sample. r is the log real return,er isthe log excess return anderp is the log excess return assuming that the riskless bond is a perpetuity. Δdisthe log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Table 8: Weighted VAR-implied regressions using d^*-p^* as the explanatory variable

	k	Coefficient	NW standard error	*t*-stats	*p*-value
Panel A r	1	0.37	0.10	3.92	0.00
	3	0.88	0.20	4.30	0.00
	5	1.18	0.27	4.39	0.00
	10	1.49	0.36	4.10	0.00
	15	1.57	0.41	3.85	0.00
	∞	1.60	0.45	3.59	0.00
Panel B er	1	0.37	0.09	3.93	0.00
	3	0.86	0.20	4.29	0.00
	5	1.16	0.26	4.37	0.00
	10	1.46	0.36	4.06	0.00
	15	1.54	0.40	3.81	0.00
	∞	1.57	0.44	3.54	0.00
Panel C erp	1	0.40	0.10	4.00	0.00
	3	0.95	0.23	4.18	0.00
	5	1.27	0.31	4.12	0.00
	10	1.61	0.44	3.69	0.00
	15	1.69	0.49	3.44	0.00
	∞	1.73	0.54	3.20	0.00
Panel D Δd	1	0.06	0.09	0.63	0.53
	3	0.13	0.21	0.63	0.53
	5	0.17	0.28	0.62	0.54
	10	0.22	0.36	0.61	0.54
	15	0.23	0.38	0.61	0.54
	∞	0.24	0.39	0.60	0.55
Panel E Δed	1	0.05	0.09	0.56	0.58
	3	0.11	0.21	0.55	0.58
	5	0.15	0.28	0.55	0.59
	10	0.19	0.36	0.54	0.59
	15	0.20	0.38	0.54	0.59
	∞	0.21	0.39	0.53	0.60
Panel F Δedp	1	0.08	0.10	0.84	0.41
	3	0.20	0.24	0.82	0.41
	5	0.27	0.33	0.81	0.42
	10	0.34	0.43	0.79	0.43
	15	0.36	0.46	0.78	0.44
	∞	0.36	0.47	0.77	0.45

Predictability coefficients for estimates of d^*-p^*under the VAR approach from the full 1931-2012sample. r is the log real return,er isthe log excess return anderp is log excess return assuming that the riskless bond is a perpetuity. Δd isthe log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth that assuming the riskless bond is a perpetuity.

Chapter 8 Out-of-Sample Forecasts

Does the observed in-sample predictability still exist out of sample? In the real world, we cannot use the regressions in Table 2 and 3 to forecast future returns. We can only use the prevailing information to estimate the future returns but we cannot use the whole sample period. Therefore, good in-sample statistical significance does not necessarily indicate a good out-of-sample forecast. The study by Goyal and Welch (2003) is probably the one of the most impressive papers that discusses the out-of-sample predictability of dividend–price ratios. They compare two strategies that forecast returns. Firstly, they run a regression, $r_{t+1} = a + b(d_t - p_t) + \varepsilon_{t+1}$, from time 1 to time t and then use $\hat{a} + \hat{b}(d_t - p_t)$ to forecast the returns at time *t+1.* Second, they calculate the sample mean returns from time 1 to time t and use these sample means to predict the returns at time *t+1.* They then compare the mean squared error of both methods. In mathematical terms, this is:

$$SSE_t = \sum_{t=1}^{T} SE(t)^{Prevailing\ \ mean} - SE(t)^{Dividen\ d\ Model}, \tag{21}$$

where $SE(t)$ is the squared out-of-sample prediction error at year $t.$ The prevailing mean SE is obtained when the prevailing up-to-date return average is used to predict the next year's real return. The conditional prediction errors of the dividend models are obtained from rolling regressions with the dividend–price ratio being the single predictor of the next year's real return.

Goyal and Welch (2003) plotted the difference between the squared prediction errors of both strategies in graph format. The results indicated that the superior performance of the dividend–price ratio model relies on the outlier effect. Once any outliers (only two outliers, in this case) are removed, the sample mean forecasts often outperform the dividend–price ratio forecasts for the U.S. data.

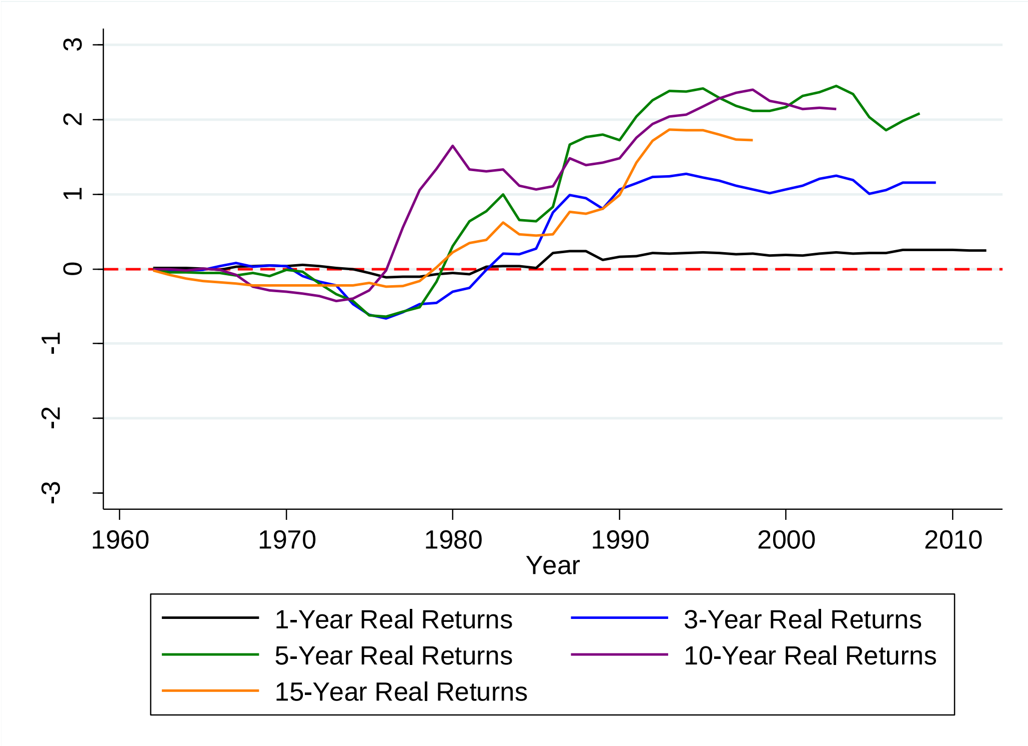
In this chapter, I follow the approach of Goyal and Welch (2003) and examine whether New Zealand's dividend–price ratios are useful for predicting returns out of sample. The main advantage of this method is that it allows us to compare predictability of different periods. It is very easy to see which strategy has the better performance for certain time periods in graph format. More importantly, as this method avoids the controversies of choosing the appropriate statistical inference, it examines the return predictability from a different angle. Unlike the approach of Goyal and Welch, which only reports out-of-sample evidence for excess returns at a 1-year horizon, this chapter reports out-of-sample forecasts for both real and excess returns at 3-, 5-, 10- and 15-year horizons. The first 30 years in the data (1931–1960) are used as the estimation period.

In Figure 3a, b and c, a positive slope indicates that dividend–price ratio regression provides better predictions than the unconditional mean predictions out of sample. In Figure 3a, we can see that the unconditional mean model slightly outperforms the dividend–price ratio model in predicting real returns from 1960 to the mid-1970s across different horizons. In addition, in the 1970s, there are more positive slopes than negative slopes at most horizons. Also, these positive slopes are very steep, indicating the much better performance of the dividend–price ratio model. Figure 3a indicates that the dividend–price ratio model generally outperforms the historical mean predictions (as most of the lines are above the red dashed line at 0) and it is clear that the real return is highly predictable after the mid-1970s.

In Figure 3b and c, we can also see evidence of the out-of-sample excess return predictability at short to medium horizons (depending on which excess return series is used). As was the case for real returns, the unconditional mean model has better predictions than the dividend–price ratio model before the mid-1970s. After the mid-1970s, there are some good and bad prediction periods for the dividend–price ratio model across time (as the lines fluctuate significantly during some periods), but the good periods outweigh the bad periods, resulting a better performance for the dividend–price ratio model at short to medium horizons. However, these good prediction periods mainly come from the mid-1970s to the late 1980s. After 1990, the unconditional model provides better predictions most of the time. At long horizons (10–15-years, depending on which excess return series is used) the dividend–price ratio model does a very poor job at forecasting excess returns, as the unconditional mean model significantly outperforms the dividend–price ratio model. Again, the noise in the bond series might be a significant factor that causes dividend–price ratio model to have poor performance at predicting excess returns.

Although more and more studies, such as those of Pástor and Stambaugh (2006) and Cochrane (2008), have found more powerful tests that produce strong evidence for in-sample return predictability, the out-of-sample forecasts have remained relatively poor (especially for U.S. data). In contrast, Figure 3a–c show that the dividend–price ratio can provide good out-of-sample predictive power for real returns at short, medium and long horizons in the New Zealand stock market. It also has some predictive power for excess returns at the short to medium horizon. The findings in Figure 3a–c reinforce the findings of Chapter 5 and demonstrate that the dividend–price ratios not only have significant in-sample predictive power for returns and excess returns, but they can also do a good job of predicting out-of-sample returns and excess returns in the New Zealand stock market. Furthermore, the results also reinforce the findings of Chapter 7, namely that every country has its unique historical events that produce financial data. While there certainly is a fundamental relationship between the variables, the predictive power of the dividend–price ratio may vary across countries. This also explains the reason why Goyal and Welch (2003) found little to no predictive power in the U.S. using the same method.

Figure 3a Cumulative Relative Out-of-Sample, Sum-Squared Error (SSE) Performance for Real Returns

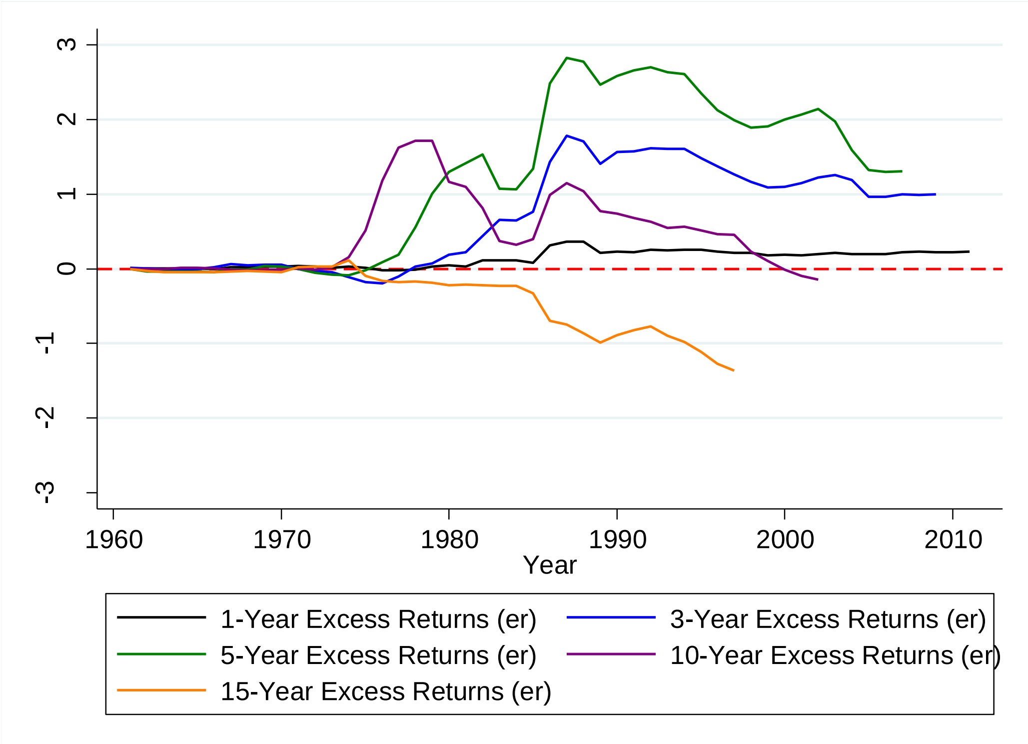


Explanation: This figure plots SSE_t, which is the cumulative sum-squared error from the unconditional model minus the cumulative sum-squared error from the dividend ratio model:

$$SSE_t = \sum_{t=1961}^{T} SE(t)^{Prevailing\ \ mean} - SE(t)^{Dividend\ \ Model},$$

where$SE(t)$ is the squared out-of-sample prediction error at year *t.* The unconditional SE is obtained when the prevailing up-to-date real return average is used to predict the next year's real return. The conditional prediction errors of the dividend models are obtained from rolling regressions with the dividend–price ratio being the single predictor of the next year's real return.

Figure 3b Cumulative Relative Out-of-Sample, Sum-Squared Error (SSE) Performance for Excess Returns (*er*)

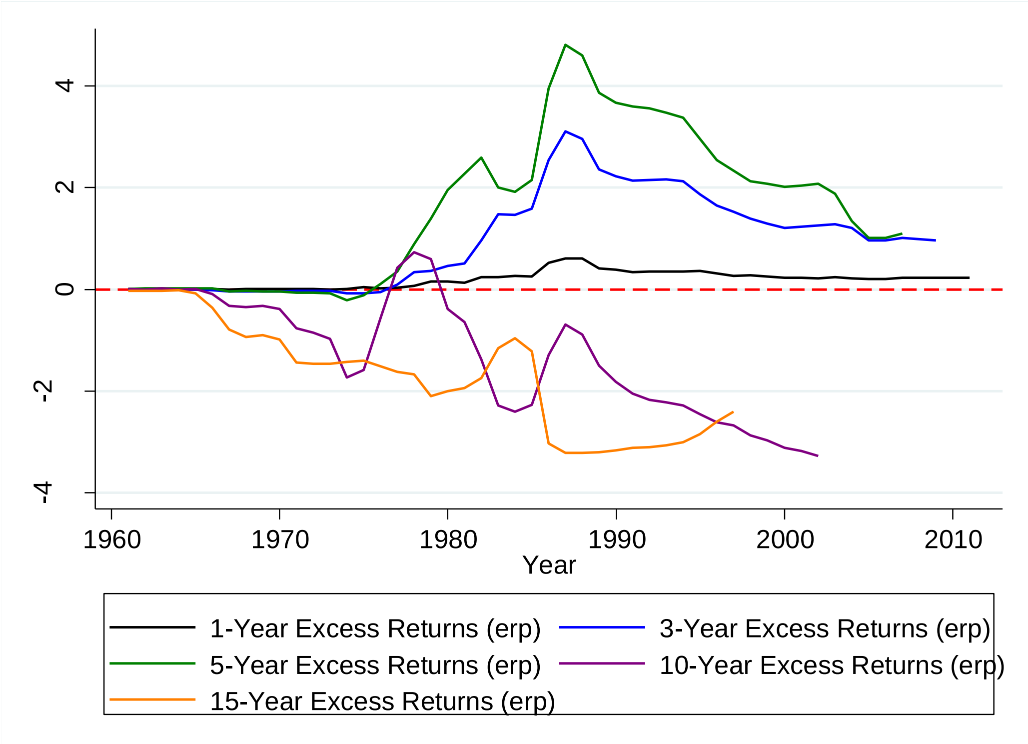


Explanation: This figure plots SSE_t, which is the cumulative sum-squared error from the unconditional model minus the cumulative sum-squared error from the dividend ratio model:

$$SSE_t = \sum_{t=1961}^{T} SE(t)^{Prevailing\ \ mean} - SE(t)^{Dividend\ \ Model},$$

where$SE(t)$ is the squared out-of-sample prediction error at year *t.* The unconditional SE is obtained when the prevailing up-to-date real return average is used to predict the next year's real return. The conditional prediction errors of the dividend models are obtained from rolling regressions with the dividend–price ratio being the single predictor of the next year's real return.

Figure 3c Cumulative Relative Out-of-Sample, Sum-Squared Error (SSE) Performance for Excess Returns (*erp*)



Explanation: This figure plots SSE_t, which is the cumulative sum-squared error from the unconditional model minus the cumulative sum-squared error from the dividend ratio model:

$$SSE_t = \sum_{t=1961}^{T} SE(t)^{Prevailing\ \ mean} - SE(t)^{Dividend\ \ Model},$$

where$SE(t)$ is the squared out-of-sample prediction error at year *t.* The unconditional SE is obtained when the prevailing up-to-date real return average is used to predict the next year's real return. The conditional prediction errors of the dividend models are obtained from rolling regressions with the dividend–price ratio being the single predictor of the next year's real return.

Chapter 9 Predictability for Individual Companies

In the previous chapters, I found that the aggregate stock returns in the New Zealand stock market are highly predictable but the aggregate dividend growth is not. The natural question is now whether the predictive power of dividend–price ratios still exists down to the individual firm level. While there is a substantial body of research for predictability at the aggregate level, firm-level predictability research is relatively scarce. Vuolteenaho (2002) is probably the only paper that carefully examines predictability at the individual firm level. Vuolteenaho decomposed the U.S. firm-level returns into an expected return component (changes in the discount rate) and a dividend growth component (changes in cash-flow expectations) using a VAR model. He found that firm-level stock returns are mainly associated with dividend growth. He also aggregated these two components for each individual firm into an equal-weight index portfolio and the findings showed that while the variance of dividend growth component was about as twice as big as that of the variance of the expected return component for firm-level returns, the variance of the dividend growth component was only three-quarters of the expected return component for the equal-weight portfolio. He concluded that cash-flow expectations are more firm-specific and that therefore the dividend growth predictability tends to be diversified in an aggregate portfolio.

This chapter aims to provide some New Zealand predictability evidence at the firm level using data from four New Zealand companies that have been continually listed since as far back as 1964: Australia and New Zealand Banking Group Limited (ANZ; 1980–2012), The Colonial Motor Company Limited (CMO; 1964–2012), Hallenstein Glasson Holdings Limited (HLG, 1972–2012) and Nuplex Industries Limited (NPX; 1970–2012). Annual data for these four companies from 1988 to 2012 were obtained from the NZX Company Research database. Data before 1988 have mainly been retrieved from *The New Zealand Financial Times* and *National Business Review*. Some data missing from *The New Zealand Financial Times* and *National Business Review* were collected from *The Press* and the *New Zealand Herald*.

This chapter investigates the predictive power of the dividend–price ratios for the four companies listed above using both the direct and VAR approaches discussed in Chapter 3. Tables 9–12 display the direct weighted results for each of the four companies.[10] For ANZ, the results show that beyond the 1-year horizon, dividend–price ratios mostly do not have any predictive power for real and excess returns. Dividend–price ratios predict future real returns at 1-year and 10-year horizons. Although the coefficient estimate for the 10-year real return regression is statistically significant, the R^2 is very small: only 4%. Dividend–price ratios also predict excess (*er* but not *erp*) returns at the 1-year horizon with a coefficient of 0.45. On the other hand, we can see from Panels D, E and F in Table 9 that all estimates for the dividend growth predictability coefficient are economically large (with the correct signs) and are statistically

[10]The unweighted results are very similar and hence are not reported.

significant at all horizons. Also the R^2 values are relatively large, with values varying from 14% to 48%. The predictive power for dividend growth increases from short (1 year) to medium horizons (3 and 5 years) and then decreases at longer horizons (10 years). The predictability for dividend growth is strongest at the medium horizon (3- to 5-year horizons), where real and excess dividend growth variation accounts for about –100% and –137% (depending on which excess return series is used) of dividend–price ratio volatility, compared with –40% and –65% for real dividend growth at k =1 and 10, respectively; –45% and –92% (depending on which excess return series is used) for excess dividend growth at k =1 and 10, respectively.

For CMO, dividend–price ratios strongly predict real and excess returns at all horizons. The return coefficient estimates are economically large and significant. The only one exception is that the 1-year excess return (*erp*) coefficient is very close to being significant: with a *p*-value of 0.07. All return regressions also have reasonably large R^2 values. This predictive power also increases with the horizon. At the 1-year horizon, the predictability is only about 12–16% for real and excess returns. This predictive power increases with the horizon and approaches 76% and 54% (*er*) at the 10-year horizon for real and excess returns, respectively. The real and excess dividend growth are mainly unpredictable for CMO: only the 10-year excess dividend growth is predictable, with the predictability approaching–27% (ed) and –43% (edp).

From Table 11, we can see that dividend–price ratios predict real and excess returns only at medium to long horizons for HGL. Dividend–price ratios only start to predict real returns from the 3-year horizon and beyond. For excess return predictability, dividend–price ratios predict *er* at the 5- and 10-year horizons, and predict *erp* only at the 10-year horizon. On the other hand, although dividend–price ratios do not predict returns at the 1-year horizon, they predict real and excess dividend growth at the 1-year horizon. At the 1-year horizon, real and excess dividend growth volatility is associated with –25%, –29% (for *ed)* or –38% (for *edp)* dividend–price ratio variation respectively. Beyond the 1-year horizon, dividend yields do not have any predictive power for dividend growth.

For NPX, dividend–price ratios do not predict real and excess returns below the 10-year horizon. The real and excess return coefficient estimates only become significant at the 10-year horizon. However, the R^2 values are tiny, with values around only 5%. Additionally, the real and excess dividend growth are very much predictable (the 5- and 10-year real dividend growth estimates are significant at 0.1; excess dividend growth estimates are significant at 0.05 for all values of *k*). However, instead of increasing in predictability, dividend growth predictability is stronger at shorter horizons and weaker at longer horizons. At the 1- and 3-year horizons, the real and excess dividend growth predictability are around –85%. This predictability decreased significantly to –46% and –55% for real and excess dividend growth (*ed)* at the 10-year horizon, respectively.

Table 9 : Direct weighted regressions for ANZ, 1980–2012

	k	Constant	Coefficient	NW standard error	t-stats	p-value	R^2
Panel A r	1	1.48	0.50	0.21	2.33	0.03	0.15
	3	0.26	0.06	0.29	0.21	0.84	0.00
	5	0.02	-0.04	0.27	-0.13	0.90	0.00
	10	1.36	0.36	0.17	2.12	0.05	0.04
Panel B er	1	1.29	0.45	0.21	2.12	0.04	0.13
	3	-0.15	-0.04	0.30	-0.13	0.89	0.00
	5	-0.49	-0.14	0.31	-0.44	0.66	0.01
	10	0.61	0.24	0.18	1.32	0.20	0.02
Panel C erp	1	0.66	0.24	0.21	1.15	0.26	0.04
	3	-0.99	-0.31	0.34	-0.92	0.37	0.04
	5	-1.04	-0.30	0.43	-0.70	0.49	0.02
	10	-0.01	0.09	0.21	0.43	0.68	0.00
Panel D Δd	1	-1.15	-0.40	0.16	-2.53	0.02	0.18
	3	-2.86	-1.01	0.29	-3.50	0.00	0.31
	5	-3.09	-1.10	0.25	-4.42	0.00	0.35
	10	-1.59	-0.65	0.16	-4.15	0.00	0.14
Panel E Δed	1	-1.33	-0.45	0.16	-2.90	0.01	0.22
	3	-3.28	-1.11	0.30	-3.66	0.00	0.37
	5	-3.59	-1.20	0.28	-4.36	0.00	0.39
	10	-2.34	-0.77	0.19	-4.11	0.00	0.17
Panel F Δedp	1	-1.97	-0.66	0.15	-4.37	0.00	0.39
	3	-4.11	-1.37	0.34	-3.99	0.00	0.48
	5	-4.15	-1.37	0.40	-3.45	0.00	0.37
	10	-2.96	-0.92	0.25	-3.71	0.00	0.21

Predictability coefficient estimates for the weighted direct approach for ANZ from 1980 to 2012. r is the log real return, er is the log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Table 10 : Direct weighted regressions for CMO,1964–2012

	k	Constant	Coefficient	NW standard error	*t*-stats	*p*-value	R^2
Panel A r	1	0.36	0.16	0.06	2.65	0.01	0.13
	3	0.72	0.34	0.09	3.67	0.00	0.29
	5	1.13	0.53	0.14	3.86	0.00	0.39
	10	1.56	0.76	0.08	9.15	0.00	0.59
Panel B er	1	0.30	0.14	0.06	2.38	0.02	0.11
	3	0.52	0.28	0.09	3.02	0.00	0.23
	5	0.80	0.44	0.14	3.24	0.00	0.31
	10	0.81	0.54	0.05	11.19	0.00	0.46
Panel C erp	1	0.25	0.12	0.06	1.88	0.07	0.07
	3	0.43	0.24	0.11	2.27	0.03	0.13
	5	0.75	0.40	0.16	2.57	0.01	0.20
	10	0.46	0.38	0.10	3.74	0.00	0.16
Panel D Δd	1	-0.26	-0.08	0.07	-1.18	0.25	0.03
	3	-0.39	-0.10	0.10	-1.00	0.32	0.02
	5	-0.24	-0.02	0.11	-0.19	0.85	0.00
	10	-0.47	-0.05	0.11	-0.48	0.63	0.00
Panel E Δed	1	-0.33	-0.10	0.07	-1.43	0.16	0.04
	3	-0.58	-0.15	0.11	-1.42	0.16	0.04
	5	-0.57	-0.11	0.12	-0.92	0.36	0.02
	10	-1.22	-0.27	0.06	-4.42	0.00	0.11
Panel F Δedp	1	-0.38	-0.12	0.08	-1.58	0.12	0.05
	3	-0.67	-0.19	0.12	-1.58	0.12	0.06
	5	-0.63	-0.15	0.15	-0.97	0.34	0.03
	10	-1.57	-0.43	0.07	-6.42	0.00	0.22

Predictability coefficient estimates for the weighted direct approach for CMO from 1964 to 2012. r is the log real return,eristhe log excess return anderp is the log excess return assuming that the riskless bond is a perpetuity. $\Delta d$is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Table 11 : Direct weighted regressions for HGL,1972–2012

	k	Constant	Coefficient	NW standard error	*t*-stats	*p*-value	R^2
Panel A r	1	0.65	0.28	0.15	1.82	0.08	0.08
	3	1.60	0.69	0.33	2.06	0.05	0.16
	5	2.42	1.04	0.46	2.27	0.03	0.25
	10	1.99	0.89	0.25	3.61	0.00	0.20
Panel B er	1	0.54	0.25	0.15	1.61	0.12	0.06
	3	1.32	0.61	0.33	1.84	0.07	0.13
	5	2.06	0.94	0.46	2.03	0.05	0.22
	10	1.51	0.80	0.22	3.62	0.00	0.19
Panel C erp	1	0.32	0.16	0.15	1.03	0.31	0.03
	3	0.89	0.42	0.34	1.25	0.22	0.07
	5	1.55	0.72	0.48	1.51	0.14	0.14
	10	1.02	0.59	0.27	2.22	0.03	0.13
Panel D Δd	1	-0.67	-0.25	0.11	-2.33	0.03	0.12
	3	-0.46	-0.15	0.42	-0.37	0.72	0.01
	5	0.24	0.15	0.50	0.29	0.77	0.01
	10	-0.06	0.05	0.32	0.16	0.88	0.00
Panel E Δed	1	-0.78	-0.29	0.11	-2.72	0.01	0.16
	3	-0.74	-0.23	0.40	-0.59	0.56	0.03
	5	-0.12	0.05	0.48	0.10	0.92	0.00
	10	-0.54	-0.05	0.26	-0.18	0.86	0.00
Panel F Δedp	1	-1.00	-0.38	0.11	-3.34	0.00	0.23
	3	-1.17	-0.42	0.39	-1.08	0.29	0.08
	5	-0.63	-0.17	0.47	-0.36	0.72	0.01
	10	-1.03	-0.25	0.26	-0.97	0.34	0.02

Predictability coefficient estimates for the weighted direct approach for HGL from 1972 to 2012. r is the log real return, er isthe log excess return and erp is the log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Table 12 : Direct weighted regressions for NPX,1970–2012

	k	Constant	Coefficient	NW standard error	*t*-stats	*p*-value	R^2
Panel A r	1	0.64	0.24	0.16	1.52	0.14	0.05
	3	-0.23	-0.02	0.27	-0.08	0.94	0.00
	5	1.05	0.46	0.36	1.28	0.21	0.03
	10	1.19	0.54	0.23	2.30	0.03	0.05
Panel B er	1	0.59	0.23	0.16	1.50	0.14	0.05
	3	-0.35	-0.04	0.24	-0.19	0.85	0.00
	5	0.77	0.39	0.30	1.33	0.19	0.03
	10	0.72	0.45	0.15	3.03	0.01	0.06
Panel C erp	1	0.64	0.25	0.16	1.53	0.13	0.06
	3	-0.29	-0.03	0.20	-0.17	0.87	0.00
	5	0.59	0.31	0.28	1.13	0.27	0.02
	10	0.45	0.33	0.15	2.23	0.03	0.03
Panel D Δd	1	-2.45	-0.84	0.15	-5.75	0.00	0.45
	3	-2.58	-0.84	0.25	-3.39	0.00	0.21
	5	-2.08	-0.64	0.35	-1.81	0.08	0.07
	10	-1.67	-0.46	0.26	-1.74	0.09	0.03
Panel E Δed	1	-2.50	-0.84	0.14	-6.01	0.00	0.47
	3	-2.70	-0.87	0.21	-4.10	0.00	0.24
	5	-2.36	-0.70	0.29	-2.42	0.02	0.09
	10	-2.14	-0.55	0.17	-3.22	0.00	0.07
Panel F Δedp	1	-2.46	-0.83	0.14	-6.01	0.00	0.47
	3	-2.64	-0.85	0.17	-4.90	0.00	0.27
	5	-2.54	-0.78	0.25	-3.11	0.00	0.11
	10	-2.41	-0.67	0.09	-7.05	0.00	0.10

Predictability coefficient estimates for the weighted direct approach for NPX from 1970 to2012. r is the log real return,eristhe log excess return anderp is the log excess return assuming that the riskless bond is a perpetuity. $\Delta d$is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity.

Tables 13–16 show the results from the implied approach. Under this approach, the returns are predictable for all four companies almost across all horizons if we relax the significance level to 0.1. The real and excess (*er*) return coefficient estimates are significant at 0.05 at all horizons for ANZ and CMO. If we use the 0.1 significance level, the real and excess (*er*) return coefficients for HGL and NPX are also significantly different from zero at different horizons (there are three exceptions: the 1-year real return for NPX and the 1-year excess return (*er*) for both HGL and NPX. But the *p*-values are not very far from the 0.1 significance level: the highest *p*-value is 0.14). Under the implied approach, we can still see a increase in return predictability with increasing time horizons but this increase is not very strong. There is an increase in return coefficients from the 1-year to the 3-year horizon for ANZ CMO and HGL, but the increase becomes smaller as the horizon increases. Moreover, from the results in Panel B and C in Tables 13–15, we can see that the null hypothesis of no return predictability is more likely to be rejected when the excess return series is calculated using the yields of the 10-year government bonds compared with assumption that the riskless bond is a perpetuity.

The real and excess dividend growth are also predictable for ANZ, HGL and NPX at all horizons. However, this dividend growth predictability does not increase significantly with increasing time horizons. Except for the increases in both the real and excess return coefficients from the 1-year to 3-year horizons for HGL, the dividend growth coefficients are almost the same across different horizons for these three companies. For CMO, real dividend growth is not predictable across all horizons, but excess dividend growth is predictable at medium to long horizons using the 0.1 significance level.

In summary, both the direct and VAR approach find mixed predictability evidence for individual companies. This is similar to what Maio and Santa-Clara (2013) found in the U.S. data. They found that dividend growth predictability tends to be strong for medium to small stocks, but the predictability of expected returns explains a large proportion of the variation in the dividend yield for large stocks. At the individual firm level, the conclusion that return predictability is the main driver of variation in the dividend–price ratio of the aggregate market portfolio does not apply. In some cases, dividend–price ratios predict returns. In other cases, dividend–price ratios predict both future returns and dividend growth. There is no situation where dividend–price ratios predict neither returns nor dividend growth. This confirms the claim by Cochrane (2008) that dividend-price ratios must predict returns or dividend growth or both, and that there must be a fundamental relationship among expected returns, future dividend growth and dividend–price ratios.

Why is it that both dividend growth and returns are predictable at the firm level but only returns are predictable at the aggregate level? One possible answer follows the arguments of Bali, Demirtas and Tehranian (2008) and Vuolteenaho (2002). Dividend growth contains two components: one is explained by the aggregate dividend growth (systematic dividend growth); the other is explained by the situation of each individual firm (unsystematic dividend growth). At the firm level, the unsystematic dividend growth can be predictable; however, when firm-level dividend growth is used to produce aggregate-level dividend growth, the unsystematic dividend growth tends to be diversified. Therefore, the aggregate dividend growth cannot be predicted. On the other hand, firm-level dividends (cash-flow) are highly correlated with future stock returns. This relationship does not vanish at the aggregate level and thus returns are predictable at the aggregate level. Another possible explanation has been provided by Leary and Michaely (2010), who argued that firms have a tendency to smooth dividend payments and therefore dividend growth is less predictable in a market in which a relatively large proportion of firms smooth their dividend payments.

Table 13: Weighted regressions implied by VAR for ANZ, 1980–2012

	k	Coefficient	NW standard error	*t*-stats	*p*-value
Panel A r	1	0.50	0.21	2.33	0.03
	3	0.55	0.18	2.99	0.00
	5	0.55	0.18	3.01	0.00
	10	0.55	0.18	3.01	0.00
	∞	0.55	0.18	3.03	0.00
Panel B er	1	0.45	0.21	2.12	0.04
	3	0.49	0.18	2.69	0.01
	5	0.49	0.18	2.71	0.01
	10	0.49	0.18	2.71	0.01
	∞	0.49	0.18	2.73	0.01
Panel C erp	1	0.24	0.21	1.15	0.26
	3	0.26	0.20	1.33	0.19
	5	0.26	0.20	1.34	0.18
	10	0.26	0.20	1.34	0.18
	∞	0.26	0.20	1.35	0.18
Panel D Δd	1	-0.40	0.16	-2.53	0.02
	3	-0.45	0.18	-2.46	0.02
	5	-0.45	0.18	-2.45	0.02
	10	-0.45	0.18	-2.45	0.02
	∞	-0.45	0.18	-2.43	0.02
Panel E Δed	1	-0.45	0.16	-2.90	0.01
	3	-0.50	0.18	-2.76	0.01
	5	-0.50	0.18	-2.75	0.01
	10	-0.50	0.18	-2.75	0.01
	∞	-0.50	0.18	-2.72	0.01
Panel F Δedp	1	-0.66	0.15	-4.37	0.00
	3	-0.73	0.19	-3.77	0.00
	5	-0.73	0.20	-3.73	0.00
	10	-0.73	0.20	-3.73	0.00
	∞	-0.73	0.20	-3.65	0.00

Predictability coefficient estimates for the weighted VAR approach for ANZ from 1980 to 2012. r is the log real return, er isthe log excess return and erp is log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity. Weight, ρ=0.948; dividend–price ratio persistence, $\emptyset = 0.10$.

Table 14: Weighted regressions implied by VAR for CMO, 1964–2012

	k	Coefficient	NW standard error	t-stats	p-value
Panel A r	1	0.16	0.06	2.65	0.01
	3	0.35	0.12	2.93	0.00
	5	0.45	0.15	3.05	0.00
	10	0.53	0.17	3.05	0.00
	∞	0.55	0.19	2.93	0.00
Panel B er	1	0.14	0.06	2.38	0.02
	3	0.31	0.12	2.61	0.01
	5	0.40	0.15	2.73	0.01
	10	0.47	0.17	2.78	0.01
	∞	0.49	0.18	2.72	0.01
Panel C erp	1	0.12	0.06	1.88	0.07
	3	0.27	0.13	2.01	0.05
	5	0.34	0.17	2.07	0.04
	10	0.41	0.19	2.11	0.04
	∞	0.42	0.20	2.10	0.04
Panel D Δd	1	-0.08	0.07	-1.18	0.25
	3	-0.19	0.15	-1.26	0.21
	5	-0.24	0.18	-1.33	0.19
	10	-0.28	0.20	-1.42	0.16
	∞	-0.29	0.20	-1.48	0.14
Panel E Δed	1	-0.10	0.07	-1.43	0.16
	3	-0.22	0.14	-1.56	0.12
	5	-0.29	0.17	-1.65	0.10
	10	-0.34	0.19	-1.78	0.08
	∞	-0.35	0.19	-1.86	0.07
Panel F Δedp	1	-0.12	0.08	-1.58	0.12
	3	-0.27	0.15	-1.72	0.09
	5	-0.34	0.19	-1.83	0.07
	10	-0.40	0.21	-1.96	0.05
	∞	-0.42	0.21	-2.03	0.05

Predictability coefficient estimates for the weighted VAR approach for CMO from 1964 to 2012. r is the log real return, er isthe log excess return and erp is log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity. Weight, ρ=0.94; dividend–price ratio persistence, $\emptyset = 0.76$.

Table 15: Weighted regressions implied by VAR for HGL, 1972–2012

	k	Coefficient	NW standard error	*t*-stats	*p*-value
Panel A r	1	0.28	0.15	1.82	0.08
	3	0.45	0.21	2.19	0.03
	5	0.49	0.21	2.33	0.02
	10	0.49	0.21	2.38	0.02
	∞	0.49	0.20	2.42	0.02
Panel B er	1	0.25	0.15	1.61	0.12
	3	0.40	0.21	1.90	0.06
	5	0.42	0.21	2.01	0.05
	10	0.43	0.21	2.05	0.04
	∞	0.43	0.21	2.09	0.04
Panel C erp	1	0.16	0.15	1.03	0.31
	3	0.25	0.22	1.14	0.26
	5	0.27	0.23	1.18	0.24
	10	0.27	0.23	1.19	0.24
	∞	0.27	0.23	1.21	0.23
Panel D Δd	1	-0.25	0.11	-2.33	0.03
	3	-0.41	0.18	-2.31	0.02
	5	-0.44	0.20	-2.24	0.03
	10	-0.45	0.20	-2.20	0.03
	∞	-0.45	0.21	-2.17	0.03
Panel E Δed	1	-0.29	0.11	-2.72	0.01
	3	-0.47	0.18	-2.67	0.01
	5	-0.50	0.20	-2.55	0.01
	10	-0.51	0.20	-2.50	0.01
	∞	-0.51	0.21	-2.45	0.02
Panel F Δedp	1	-0.38	0.11	-3.34	0.00
	3	-0.61	0.19	-3.27	0.00
	5	-0.66	0.21	-3.08	0.00
	10	-0.66	0.22	-2.99	0.00
	∞	-0.66	0.23	-2.91	0.00

Predictability coefficient estimates for the weighted VAR approach for HGL from 1972 to 2012. r is the log real return, er isthe log excess return and erp is log excess return assuming that the riskless bond is a perpetuity. Δd is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity. Weight, ρ=0.923; dividend–price ratio persistence, $\emptyset = 0.46$.

Table 16: Weighted regressions implied by VAR for NPX, 1970–2012

	k	Coefficient	NW standard error	*t*-stats	*p*-value
Panel A *r*	1	0.24	0.16	1.52	0.14
	3	0.23	0.13	1.69	0.10
	5	0.23	0.13	1.69	0.10
	10	0.23	0.13	1.69	0.10
	∞	0.23	0.13	1.70	0.09
Panel B *er*	1	0.23	0.16	1.50	0.14
	3	0.22	0.13	1.67	0.10
	5	0.22	0.13	1.67	0.10
	10	0.22	0.13	1.67	0.10
	∞	0.22	0.13	1.68	0.10
Panel C *erp*	1	0.25	0.16	1.53	0.13
	3	0.23	0.13	1.73	0.09
	5	0.23	0.13	1.73	0.09
	10	0.23	0.13	1.73	0.09
	∞	0.23	0.13	1.74	0.09
Panel D Δd	1	-0.84	0.15	-5.75	0.00
	3	-0.78	0.13	-5.86	0.00
	5	-0.78	0.13	-5.83	0.00
	10	-0.78	0.13	-5.82	0.00
	∞	-0.78	0.14	-5.72	0.00
Panel E Δed	1	-0.84	0.14	-6.01	0.00
	3	-0.79	0.13	-6.08	0.00
	5	-0.79	0.13	-6.04	0.00
	10	-0.79	0.13	-6.04	0.00
	∞	-0.79	0.13	-5.92	0.00
Panel F Δedp	1	-0.83	0.14	-6.01	0.00
	3	-0.77	0.13	-5.84	0.00
	5	-0.77	0.13	-5.81	0.00
	10	-0.77	0.13	-5.81	0.00
	∞	-0.77	0.14	-5.69	0.00

Predictability coefficient estimates for the weighted VAR approach for NPX from 1970 to 2012. r is the log real return,eristhe log excess return anderp is log excess return assuming that the riskless bond is a perpetuity. $\Delta d$is the log real dividend growth, Δed is the log excess dividend growth and Δedp is the log excess dividend growth assuming that the riskless bond is a perpetuity. Weight,ρ=0.947; dividend–price ratio persistence,$\emptyset =$ –0.08.

Chapter 10 Conclusion

There is a general conviction that variation in dividend–price ratios is associated with the expected returns but not with expected dividend growth (i.e., returns are predictable but dividend growth is not). However, most of the evidence comes from the U.S. and this topic has not been carefully examined in the New Zealand stock market. This research tries to fill this gap and investigates the predictive power of dividend yields on stock returns using the New Zealand stock market data from 1930 to 2012. The results from both the direct regression and VAR approach confirm that the general conclusion in the literature in New Zealand data: real (or excess) returns are predictable at short, medium and long horizons by dividend–price ratios, but real (or excess) dividend growth is not.

Return predictability is generally accepted in the literature; however, the interpretation of it is contentious. Return predictability can be potentially associated with either risk-pricing or irrational mispricing. On the basis of the idea that if mispricing is the cause of the observed predictability, we should see a fall in the estimated return coefficients when mispricing is substantially reduced in the market. This research divides the New Zealand stock market data in to two sub-samples separated by the financial sector reform which happened in 1984. By comparing the return coefficients from these two sub-samples, the results suggest that the return predictability in the New Zealand stock market is not primarily due to mispricing.

Furthermore, this research also examines the influence of historical events on return predictability. While there is a certain fundamental relationship between dividend–price ratio and returns (or excess returns), it seems that the influence of historical events has outweighed this relationship in the New Zealand data. This finding is similar to that of Cornell (2013) for the U.S. data, suggesting that the observed return predictability patterns may not hold in the future once the influence of some future events overwhelms the fundamental relationship between the variables. The results also suggest that we need to pay more attention to the influence of historical events in terms of dividend yields and return predictability research.

Furthermore, in addition to examining the in-sample predictability, this research also examines the out-of-sample predictive power of dividend–price ratios. Unlike the out-of-sample tests on the U.S. data, which commonly report poor out-of-sample predictability for dividend–price ratios, this research finds that dividend–price ratios have strong out-of-sample predictive power for real returns at short, medium and long horizons. Dividend–price ratios also show some good out-of-sample predictive power for excess returns at short to medium horizons.

Finally, this research also tries to answer the question whether the predictive power of dividend–price ratios still exists down to the individual firm level. By using the data on four continually listed companies in the New Zealand stock market, the results suggest that the predictive power of dividend–price ratios is mixed at the firm level. For some firms, dividend–price ratios predict future returns. For other firms, dividend–price ratios predict future dividend growth or both. The results also suggest that the common perception that return predictability is the main driver of variation in the dividend–price ratio of the aggregate market portfolio does not apply at the firm level. The predictability of firm-level dividend growth vanishes at the aggregate level. On the other hand, the strong relationship between dividend payments, price and future returns also holds at the aggregate level, and thus future returns are still predictable.

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Appendices

Appendix A

To compute the standard errors for the implied long-horizon coefficients, b_i^k $(i = r, d \; or \; d - p)$, the Delta method is used:

$$Var\left(b_i^k\right) = \left(\frac{\partial b_i^k}{d b_i}\right) \cdot \Sigma \cdot \left(\frac{\partial b_i^k}{d b_i}\right)^T.$$

The unweighted long-horizon coefficients can be written as:

$$b_r^{(k)} = b_r \frac{1-\emptyset^k}{1-\emptyset};$$

$$b_d^{(k)} = b_d \frac{1-\emptyset^k}{1-\emptyset};$$

$$b_{dp}^{(k)} = \emptyset^k.$$

Therefore:

$$Var\left(b_r^{(k)}\right) = \begin{bmatrix} \frac{\partial b_r^{(k)}}{\partial b_r} & \frac{\partial b_r^{(k)}}{\partial \emptyset} \end{bmatrix} \begin{bmatrix} Var(b_r) & cov(b_r, \emptyset) \\ cov(b_r, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{\partial b_r^{(k)}}{\partial b_r} \\ \frac{\partial b_r^{(k)}}{\partial \emptyset} \end{bmatrix} =$$

$$\begin{bmatrix} \frac{1-\emptyset^k}{1-\emptyset} & \frac{-k b_r \emptyset^{k-1}(1-\emptyset)+b_r\left(1-\emptyset^k\right)}{(1-\emptyset)^2} \end{bmatrix} \begin{bmatrix} Var(b_r) & cov(b_r, \emptyset) \\ cov(b_r, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{1-\emptyset^k}{1-\emptyset} \\ \frac{-k b_r \emptyset^{k-1}(1-\emptyset)+b_r\left(1-\emptyset^k\right)}{(1-\emptyset)^2} \end{bmatrix},$$

$$Var\left(b_d^{(k)}\right) = \begin{bmatrix} \frac{\partial b_d^{(k)}}{\partial b_d} & \frac{\partial b_d^{(k)}}{\partial \emptyset} \end{bmatrix} \begin{bmatrix} Var(b_d) & cov(b_d, \emptyset) \\ cov(b_d, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{\partial b_d^{(k)}}{\partial b_d} \\ \frac{\partial b_d^{(k)}}{\partial \emptyset} \end{bmatrix} =$$

$$\begin{bmatrix} \frac{1-\emptyset^k}{1-\emptyset} & \frac{-kb_d\emptyset^{k-1}(1-\emptyset)+b_d(1-\emptyset^k)}{(1-\emptyset)^2} \end{bmatrix} \begin{bmatrix} Var(b_d) & cov(b_d,\emptyset) \\ cov(b_d,\emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{1-\emptyset^k}{1-\emptyset} \\ \frac{-kb_d\emptyset^{k-1}(1-\emptyset)+b_d(1-\emptyset^k)}{(1-\emptyset)^2} \end{bmatrix}$$

and:

$$Var\left(b_{d-p}^{(k)}\right) = \left(\frac{\partial b_{dp}^{(k)}}{\partial \emptyset}\right)^2 \cdot Var(\emptyset).$$

The weighted long-horizon coefficients can be written as:

$$b_r^{(k)} = b_r \frac{1-(\rho\emptyset)^k}{1-\rho\emptyset};$$

$$b_d^{(k)} = b_d \frac{1-(\rho\emptyset)^k}{1-\rho\emptyset};$$

$$b_{dp}^{(k)} = (\rho\emptyset)^k.$$

Therefore:

$$Var(b_r^{(k)}) = \begin{bmatrix} \frac{\partial b_r^{(k)}}{\partial b_r} & \frac{\partial b_r^{(k)}}{\partial \rho} & \frac{\partial b_r^{(k)}}{\partial \emptyset} \end{bmatrix} \begin{bmatrix} Var(b_r) & cov(b_r,\rho) & cov(b_r,\emptyset) \\ cov(b_r,\rho) & Var(\rho) & cov(\rho,\emptyset) \\ cov(b_r,\emptyset) & cov(\rho,\emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{\partial b_r^{(k)}}{\partial b_r} \\ \frac{\partial b_r^{(k)}}{\partial \rho} \\ \frac{\partial b_r^{(k)}}{\partial \emptyset} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1-\rho^k\emptyset^k}{1-\rho\emptyset} & \frac{-kb_r\rho^{k-1}\emptyset^k(1-\rho\emptyset)+\emptyset b_r(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} & \frac{-kb_r\rho^k\emptyset^{k-1}(1-\rho\emptyset)+\rho b_r(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \end{bmatrix}$$

$$\cdot \begin{bmatrix} Var(b_r) & cov(b_r,\rho) & cov(b_r,\emptyset) \\ cov(b_r,\rho) & Var(\rho) & cov(\rho,\emptyset) \\ cov(b_r,\emptyset) & cov(\rho,\emptyset) & Var(\emptyset) \end{bmatrix}$$

$$\cdot \begin{bmatrix} \frac{1-\rho^k\emptyset^k}{1-\rho\emptyset} \\ \frac{-kb_r\rho^{k-1}\emptyset^k(1-\rho\emptyset)+\emptyset b_r(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \\ \frac{-kb_r\rho^k\emptyset^{k-1}(1-\rho\emptyset)+\rho b_r(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \end{bmatrix},$$

$$Var(b_d^{(k)}) = \left[\frac{\partial b_d^{(k)}}{\partial b_d}, \frac{\partial b_d^{(k)}}{\partial \rho}, \frac{\partial b_d^{(k)}}{\partial \emptyset}\right] \begin{bmatrix} Var(b_d) & cov(b_d, \rho) & cov(b_d, \emptyset) \\ cov(b_d, \rho) & Var(\rho) & cov(\rho, \emptyset) \\ cov(b_d, \emptyset) & cov(\rho, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{\partial b_d^{(k)}}{\partial b_d} \\ \frac{\partial b_d^{(k)}}{\partial \rho} \\ \frac{\partial b_d^{(k)}}{\partial \emptyset} \end{bmatrix}$$

$$= \left[\frac{1-\rho^k\emptyset^k}{1-\rho\emptyset} \quad \frac{-kb_d\rho^{k-1}\emptyset^k(1-\rho\emptyset)+\emptyset b_d(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \quad \frac{-kb_d\rho^k\emptyset^{k-1}(1-\rho\emptyset)+\rho b_d(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2}\right] \cdot$$

$$\cdot \begin{bmatrix} Var(b_d) & cov(b_d, \rho) & cov(b_d, \emptyset) \\ cov(b_d, \rho) & Var(\rho) & cov(\rho, \emptyset) \\ cov(b_d, \emptyset) & cov(\rho, \emptyset) & Var(\emptyset) \end{bmatrix}$$

$$\cdot \begin{bmatrix} \frac{1-\rho^k\emptyset^k}{1-\rho\emptyset} \\ \frac{-kb_d\rho^{k-1}\emptyset^k(1-\rho\emptyset)+\emptyset b_d(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \\ \frac{-kb_d\rho^k\emptyset^{k-1}(1-\rho\emptyset)+\rho b_d(1-\rho^k\emptyset^k)}{(1-\rho\emptyset)^2} \end{bmatrix},$$

and:

$$\mathrm{Var}\left(b_{d-p}^{(k)}\right) = \begin{bmatrix} \frac{\partial b_{dp}^{(k)}}{\partial \rho} & \frac{\partial b_{dp}^{(k)}}{\partial \emptyset} \end{bmatrix} \begin{bmatrix} Var(\rho) & cov(\rho, \emptyset) \\ cov(\rho, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} \frac{\partial b_{dp}^{(k)}}{\partial \rho} \\ \frac{\partial b_{dp}^{(k)}}{\partial \emptyset} \end{bmatrix}$$

$$= [k\rho^{k-1}\emptyset^k \quad k\rho^k\emptyset^{k-1}] \begin{bmatrix} Var(\rho) & cov(\rho, \emptyset) \\ cov(\rho, \emptyset) & Var(\emptyset) \end{bmatrix} \begin{bmatrix} k\rho^{k-1}\emptyset^k \\ k\rho^k\emptyset^{k-1} \end{bmatrix}.$$

As Equation (4) in Chapter 3 indicates that $1 \approx b_r^k - b_{\Delta d}^k + \rho^k b_{d-p}^k$, the covariance between each variable involved in the delta method can therefore be derived using this identity

Appendix B

The dividend–price ratio is calculated as the difference in returns between the Gross index (which includes capital gains and cash dividends) and the capital index (which includes capital gains only). Therefore the dividend–price ratio at the end of each year is:

$$\frac{D_t}{P_t} = (\frac{D_t+P_t}{P_{t-1}} - \frac{P_t}{P_{t-1}}) \times \frac{P_{t-1}}{P_t}.$$

The dividend growth for each year is calculated as follows:

$$\Delta\, D_t = \frac{\frac{D_t}{P_t} \times P_t}{\frac{D_{t-1}}{P_{t-1}} \times P_{t-1}} - 1.$$

Appendix C

Table 1C: Pre-reform robustness test for 1-year real returns

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.23	0.12	1.92	0.07	0.22	20
1931–51	0.26	0.10	2.62	0.02	0.26	21
1931–52	0.26	0.12	2.25	0.04	0.26	22
1931–53	0.27	0.12	2.31	0.03	0.26	23
1931–54	0.27	0.12	2.31	0.03	0.26	24
1931–55	0.27	0.12	2.31	0.03	0.26	25
1931–56	0.27	0.12	2.37	0.03	0.27	26
1931–57	0.27	0.12	2.33	0.03	0.24	27
1931–58	0.30	0.12	2.55	0.02	0.24	28
1931–59	0.31	0.12	2.57	0.02	0.24	29
1931–60	0.32	0.12	2.66	0.01	0.24	30
1931–61	0.32	0.12	2.69	0.01	0.24	31
1931–62	0.33	0.12	2.82	0.01	0.26	32
1931–63	0.33	0.12	2.84	0.01	0.26	33
1952–84	0.26	0.15	1.82	0.08	0.10	33
1953–84	0.28	0.15	1.89	0.07	0.11	32
1954–84	0.29	0.15	1.97	0.06	0.12	31
1955–84	0.30	0.15	2.00	0.06	0.12	30
1956–84	0.30	0.15	1.99	0.06	0.12	29
1957–84	0.32**	0.15	2.08	0.05	0.13	28
1958–84	0.30	0.16	1.95	0.06	0.12	27
1959–84	0.33*	0.15	2.18	0.04	0.15	26
1960–84	0.36**	0.15	2.33	0.03	0.16	25
1961–84	0.35	0.16	2.17	0.04	0.15	24
1962–84	0.38**	0.16	2.28	0.03	0.16	23
1963–84	0.41*	0.16	2.50	0.02	0.19	22
1964–84	0.44*	0.16	2.70	0.01	0.21	21
1965–84	0.45*	0.18	2.55	0.02	0.20	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.

Table 2C: Pre-reform robustness test for 3-year real returns

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.70	0.17	4.19	0.00	0.54	20
1931–51	0.68	0.15	4.47	0.00	0.53	21
1931–52	0.68	0.15	4.64	0.00	0.52	22
1931–53	0.68	0.14	4.74	0.00	0.52	23
1931–54	0.68	0.14	4.80	0.00	0.51	24
1931–55	0.68	0.14	4.73	0.00	0.51	25
1931–56	0.69	0.14	4.99	0.00	0.50	26
1931–57	0.70	0.14	5.13	0.00	0.49	27
1931–58	0.72	0.13	5.37	0.00	0.50	28
1931–59	0.72	0.13	5.36	0.00	0.50	29
1931–60	0.71	0.13	5.35	0.00	0.48	30
1931–61	0.72	0.13	5.53	0.00	0.48	31
1931–62	0.72	0.13	5.57	0.00	0.48	32
1931–63	0.71	0.13	5.46	0.00	0.46	33
1952–84	0.46*	0.29	1.59	0.12	0.13	33
1953–84	0.49*	0.29	1.66	0.11	0.14	32
1954–84	0.50*	0.30	1.69	0.10	0.14	31
1955–84	0.52*	0.30	1.73	0.09	0.15	30
1956–84	0.52*	0.31	1.70	0.10	0.14	29
1957–84	0.55*	0.31	1.79	0.09	0.16	28
1958–84	0.59**	0.31	1.93	0.07	0.18	27
1959–84	0.62**	0.31	2.03	0.05	0.20	26
1960–84	0.64**	0.31	2.07	0.05	0.20	25
1961–84	0.71	0.31	2.31	0.03	0.23	24
1962–84	0.77	0.30	2.59	0.02	0.26	23
1963–84	0.80	0.30	2.69	0.01	0.28	22
1964–84	0.82**	0.31	2.68	0.02	0.27	21
1965–84	0.79	0.33	2.40	0.03	0.24	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.

Table 3C: Pre-reform robustness test for 5-year real returns

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.79	0.09	8.48	0.00	0.64	20
1931–51	0.75	0.08	9.31	0.00	0.61	21
1931–52	0.76	0.08	9.74	0.00	0.57	22
1931–53	0.76	0.08	9.78	0.00	0.58	23
1931–54	0.76	0.08	9.54	0.00	0.55	24
1931–55	0.76	0.09	8.91	0.00	0.51	25
1931–56	0.77	0.09	8.45	0.00	0.51	26
1931–57	0.78	0.10	8.04	0.00	0.51	27
1931–58	0.82	0.13	6.50	0.00	0.50	28
1931–59	0.83	0.13	6.21	0.00	0.49	29
1931–60	0.82	0.13	6.18	0.00	0.49	30
1931–61	0.82	0.13	6.23	0.00	0.49	31
1931–62	0.80	0.12	6.66	0.00	0.47	32
1931–63	0.79	0.12	6.77	0.00	0.46	33
1952–84	0.63*	0.33	1.90	0.07	0.14	33
1953–84	0.66**	0.33	1.99	0.06	0.15	32
1954–84	0.67**	0.34	1.99	0.06	0.16	31
1955–84	0.71	0.34	2.10	0.05	0.17	30
1956–84	0.77	0.34	2.25	0.03	0.19	29
1957–84	0.80	0.34	2.32	0.03	0.20	28
1958–84	0.84	0.35	2.43	0.02	0.22	27
1959–84	0.89**	0.34	2.60	0.02	0.25	26
1960–84	0.95*	0.34	2.79	0.01	0.27	25
1961–84	1.04*	0.34	3.03	0.01	0.30	24
1962–84	1.09*	0.34	3.19	0.00	0.32	23
1963–84	1.11*	0.35	3.16	0.01	0.32	22
1964–84	1.16*	0.35	3.37	0.00	0.33	21
1965–84	1.30*	0.31	4.26	0.00	0.37	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.

Table 4C: Pre-reform robustness test for 1-year excess returns (*er*)

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.08	0.13	0.58	0.57	0.03	20
1931–51	0.12	0.14	0.89	0.39	0.07	21
1931–52	0.12	0.14	0.89	0.39	0.07	22
1931–53	0.12	0.14	0.92	0.37	0.07	23
1931–54	0.12	0.14	0.92	0.37	0.07	24
1931–55	0.12	0.13	0.93	0.36	0.07	25
1931–56	0.13	0.13	0.96	0.35	0.08	26
1931–57	0.12	0.13	0.94	0.36	0.07	27
1931–58	0.16	0.14	1.14	0.26	0.08	28
1931–59	0.16	0.14	1.16	0.26	0.08	29
1931–60	0.17	0.14	1.24	0.22	0.09	30
1931–61	0.17	0.14	1.26	0.22	0.09	31
1931–62	0.19	0.14	1.36	0.18	0.10	32
1931–63	0.19	0.14	1.37	0.18	0.10	33
1952–84	0.31*	0.12	2.55	0.02	0.18	33
1953–84	0.33*	0.12	2.66	0.01	0.19	32
1954–84	0.34*	0.12	2.74	0.01	0.20	31
1955–84	0.35*	0.13	2.76	0.01	0.20	30
1956–84	0.36*	0.13	2.76	0.01	0.20	29
1957–84	0.37*	0.13	2.83	0.01	0.21	28
1958–84	0.35*	0.13	2.69	0.01	0.20	27
1959–84	0.38*	0.13	2.96	0.01	0.24	26
1960–84	0.40*	0.13	3.08	0.01	0.25	25
1961–84	0.39*	0.14	2.83	0.01	0.23	24
1962–84	0.41*	0.14	2.90	0.01	0.24	23
1963–84	0.43*	0.14	3.12	0.01	0.26	22
1964–84	0.46*	0.14	3.33	0.00	0.28	21
1965–84	0.45*	0.15	3.05	0.01	0.26	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.

Table 5C: Pre-reform robustness test for 3-year excess returns (*er*)

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.42	0.11	3.77	0.00	0.40	20
1931–51	0.40	0.10	4.10	0.00	0.39	21
1931–52	0.41	0.09	4.33	0.00	0.37	22
1931–53	0.41	0.09	4.42	0.00	0.37	23
1931–54	0.41	0.09	4.47	0.00	0.37	24
1931–55	0.41	0.09	4.36	0.00	0.36	25
1931–56	0.42	0.09	4.63	0.00	0.36	26
1931–57	0.42	0.09	4.76	0.00	0.35	27
1931–58	0.44	0.09	4.89	0.00	0.36	28
1931–59	0.43	0.09	4.83	0.00	0.35	29
1931–60	0.43	0.09	4.89	0.00	0.35	30
1931–61	0.44	0.09	5.03	0.00	0.35	31
1931–62	0.44	0.09	5.04	0.00	0.35	32
1931–63	0.43	0.09	4.83	0.00	0.31	33
1952–84	0.61*	0.23	2.66	0.01	0.29	33
1953–84	0.63*	0.23	2.77	0.01	0.31	32
1954–84	0.64*	0.23	2.80	0.01	0.31	31
1955–84	0.66*	0.23	2.83	0.01	0.32	30
1956–84	0.66*	0.24	2.77	0.01	0.31	29
1957–84	0.68*	0.24	2.89	0.01	0.33	28
1958–84	0.72*	0.24	3.04	0.01	0.35	27
1959–84	0.74*	0.24	3.13	0.01	0.37	26
1960–84	0.74*	0.24	3.11	0.01	0.36	25
1961–84	0.79*	0.24	3.30	0.00	0.37	24
1962–84	0.84*	0.24	3.58	0.00	0.41	23
1963–84	0.86*	0.24	3.63	0.00	0.41	22
1964–84	0.85*	0.24	3.53	0.00	0.40	21
1965–84	0.79*	0.26	3.07	0.01	0.34	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.

Table 6C: Pre-reform robustness test for 5-year excess returns (*er*)

Year	Coefficient	NW standard error	*t*-stats	*p*-value	R^2	No. of obs
1931–50	0.44	0.10	4.37	0.00	0.38	20
1931–51	0.43	0.09	4.62	0.00	0.38	21
1931–52	0.43	0.09	4.85	0.00	0.35	22
1931–53	0.43	0.09	4.89	0.00	0.35	23
1931–54	0.43	0.09	4.95	0.00	0.33	24
1931–55	0.43	0.09	4.93	0.00	0.31	25
1931–56	0.43	0.09	4.95	0.00	0.32	26
1931–57	0.44	0.09	4.93	0.00	0.32	27
1931–58	0.47	0.10	4.50	0.00	0.32	28
1931–59	0.47	0.11	4.47	0.00	0.32	29
1931–60	0.48	0.11	4.45	0.00	0.33	30
1931–61	0.47	0.10	4.56	0.00	0.32	31
1931–62	0.45	0.10	4.68	0.00	0.28	32
1931–63	0.44	0.09	4.68	0.00	0.28	33
1952–84	0.74*	0.25	2.90	0.01	0.27	33
1953–84	0.77*	0.25	3.05	0.01	0.28	32
1954–84	0.77*	0.25	3.04	0.01	0.28	31
1955–84	0.81*	0.25	3.21	0.00	0.30	30
1956–84	0.85*	0.25	3.44	0.00	0.32	29
1957–84	0.87*	0.25	3.51	0.00	0.33	28
1958–84	0.89*	0.25	3.62	0.00	0.33	27
1959–84	0.93*	0.24	3.81	0.00	0.36	26
1960–84	0.96*	0.24	3.97	0.00	0.37	25
1961–84	1.01*	0.25	4.07	0.00	0.38	24
1962–84	1.03*	0.25	4.12	0.00	0.38	23
1963–84	1.03*	0.26	3.98	0.00	0.37	22
1964–84	1.05*	0.26	4.03	0.00	0.37	21
1965–84	1.13*	0.25	4.56	0.00	0.38	20

The coefficients were obtained using the direct approach. * and ** indicate that the latter sub-period coefficient is not greater than the earlier sub-period coefficient at the 0.05 and 0.1 level, respectively.